Biomedical Image Segmentation and Analysis in Deep Learning

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ABSTRACT Biomedical Image Processing, such as human organ segmentation and disease analysis, is a modern field in medicine development and patient treatment. Besides there are many kinds of image formats, the diversity and complexity of biomedical data is still a big issue to all of researchers in their applications. In order to deal with the problem, deep learning give us a successful and effective solutions. Unet and LSTM are two general approaches to the most of case of medical image data. While Unet helps to teach a machine in learning data from each image accompanied with its labelled information, LSTM helps to remember states from many slices of images by times. Unet gives us the segmentation of tumor, abnormal things from biomedical images and then the LSTM gives us the effective diagnosis on a patient disease. In this paper, we show some scenarios of using Unets and LSTM to segment and analysis on many kinds of human organ images and results of brain, retinal, skin, lung and breast segmentation.

KEYWORDS

Image Segmentation, Deep Learning, U-net, Long Short-Term Memory

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INTRODUCTION

Biomedical image concentrates on the process from capturing an image on specific device, making a diagnosis on them, to giving treatment to a patient. The segmentation of each part in a biomedical image plays a crucial role in the whole process. If the segmentation is incorrect, the result leads to the wrong diagnosis and treatment. The big issue in segmentation in this field is that the boundary is sometime not clearly. For example, in a brain image, the changing intensity from white matter(WM) to gray matter(GM), or from gray matter (GM) to Cerebrospinal Fluid (CSF) is very sensitive and gradually. In computer vision, there are a lot of segmentation techniques such as Expectation Maximization, WaterShed, and Superpixels etc... but it just suitable to some biomedical images and get failure in the other images. For that reason, deep learning is the optimal and promising approach. Deep learning generally comprises a convolution step to extract feature from image and neural network to learn how to segment from the feature. [1, 2]

U-Net is a convolutional neural network that was developed for biomedical image segmentation. It was introduced by Computer

Science Department of the University of Freiburg, Germany [3] The network architecture was modified and extended to work with fewer training images and to yield more precise segmentations. Based on a biomedical image and its mask, Unet can help us to decide which pixels are object and which pixels are not. As a result, we can get a semantic segmentation even the boundary is not clear. Long short-term memory (LSTM) is an artificial recurrent neural network (RNN) architecture [4] used in the field of deep learning. It can not only process single data points (such as images), but also entire sequences of data. Slices of biomedical images are a sequence of information in which the connection information can reveal us about periodic states of patients.

In this paper, we introduce some scenarios using Unets and LSTM in some biomedical applications such as brain, retinal eye, skin, lung and breast image. In brain image, we need to segment White Matter (WM), gray matter (GM), Cerebrospinal Fluid (CSF), and tumor from an input image. In retinal image, we need to segment Exudates and Hemorrhages, and then check the relationship between them and diabetes. In skin image, we need to segment melanoma region and make diagnosis about malignant or benign state. In skin image, melanoma region is segmented and ABCD's

Figure 1 U-Net deep learning architecture

feature is calculated to distinguish malignant state from benign state. In lung image, left and right lung is segmented first and the sequence of slices is learned by LSTM to predict the abnormal exhalation and inhalation state. In breast image, tumor position is segmented from many candidate regions look like tumor.

UNETS AND LSTM

Unets' Deep Learning in Segmentation

Unets is a semantic segmentation approach which helps to segment object by pixels. It consists of two paths: contraction path and expansion path. The contraction can help to extract feature and reduce the size of feature map. The feature extraction is constructed depending on the traditional convolution nets with 3 x 3 convolution and 2 x 2 max pooling. The opposite path named expansion path is the key point of Unets. With the 2 x 2 up convolution, it can recover the size of segmentation map. The concatenation of feature maps at the same level helps to localize information from contraction path to expansion path.

Unets is applied mostly in biomedical image, because it gives a feature map from each level and it ensure that the sensitive intensity is decided belongs to object or not depending on the feature map. The feature map is correctly ensured by the contraction path [5, 6].

LSTM Deep Learning in Diagnosis

LSTM (Long Short Term Memory networks) is developed from recurrent network with forget gate, input gate, and output gate at each cell in network. LSTM has an ability to remember information for a long periods of time as its behaviors. The forget gate is to decide which information is kept and which one is get rid of from the feature line. The input gate decides which values the network will update. And the last output gate, the network will calculate the output information to the next time.

LSTM can be used to remember all information by time. If we consider index's slices of biomedical images as time. The change of tumor or abnormal things can be captured and remembered to decide the state of disease. The diagnosis will be become more accurate than if we only look at one slice or each slice one by one.

Figure 2 LSTM Cell Architecture

Figure 3 Scenario for Biomedical Image Segmentation using Unets

PROPOSED SCENARIOS

Scenario for segmentation

The scenario for biomedical image segmentation is controlled by many steps. The first step is that an input image need to be normalized and adjusted by intensity and illumination. The compensation is very important for Unets to get a higher accuracy than the raw data. The second step is that feature extraction by convolution network is processed. The loss function in back propagation is ensured that the segmentation error is lowest and the loss is minimum. In the last step is the test step, the built model with learned weights can segment any objects with tight boundary correctly depending on the number of training data which is inputted in the training step.

Figure 4 Scenario for Biomedical Image Diagnosis using LSTM

Figure 5 Example of ABCD criteria for melanoma diagnosis in malignant or benign state

Scenario for diagnosis

LSTM starts the scenario with feature extraction. Each biomedical image has different features. For example, in skin image, the melanoma can be classified into malignant or benign based on ABCD features where A is asymmetry, B is border irregularity, C is Color, D is diameter. And then some regularization is applied to make sure that the result is not overfitting and the convergence is faster. The number of layer LSTM is followed to catch and remember as much as information between slices. The output layer is a softmax to give the probabilities of desired diagnosis types (such as probabilities of malignant or benign state) [7]

EXPERIMENTAL RESULTS

The result of biomedical image segmentation and diagnosis are showed below. The two scenarios of segmentation and diagnosis is processed on each type of image.

Brain Images

White matter hyperintensities is a term you might hear used to describe spots in the brain that show up on magnetic resonance imaging (MRIs) as bright white areas. According to Charles DeCarli, the director of UC Davis Alzheimer's Disease Center, these areas may indicate some type of injury to the brain, perhaps due to decreased blood flow in that area. The presence of white matter hyperintensities has been correlated with a higher risk of stroke, which can lead to vascular dementia.

Grey matter (or gray matter) is a major component of the central nervous system, consisting of neuronal cell bodies, neuropil (dendrites and myelinated as well as unmyelinated axons), glial cells (astrocytes and oligodendrocytes), synapses, and capillaries. Grey matter is distinguished from white matter in that it contains numerous cell bodies and relatively few myelinated axons, while white matter contains relatively few cell bodies and is composed chiefly of long-range myelinated axon tracts. The colour difference arises mainly from the whiteness of myelin. In living tissue, grey matter actually has a very light grey colour with yellowish or pinkish hues, which come from capillary blood vessels and neuronal cell bodies.

Cerebrospinal fluid (CSF) spaces include ventricles and cerebral and spinal subarachnoid spaces. CSF motion is a combined effect of CSF production rate and superimposed cardiac pulsations.

Figure 6 Brain Image Segmentation into WM, GM, and CSF

Figure 7 Retinal Image Segmentation into Hemorrhages and Exudates

Knowledge of CSF dynamics has benefited considerably from the development of phase-contrast (PC) MRI. There are several disorders such as communicating and non-communicating hydrocephalus, Chiari malformation, syringomyelic cyst and arachnoid cyst that can change the CSF dynamics. The aims of this pictorial review are to outline the PC MRI technique, CSF physiology and cerebrospinal space anatomy, to describe a group of congenital and acquired disorders that can alter the CSF dynamics, and to assess the use of PC MRI in the assessment of various central nervous system abnormalities.

Retinal Images

Diabetic retinopathy is a complication of diabetes mellitus affects the retina which causes retinal damage, resulting in blurred vision and ultimately blindness. 90% of people with diabetes over 10 years have diabetic retinopathy. Diabetic retinopathy consists of three stages: background diabetic retinopathy, non-proliferative diabetic retinopathy, proliferative diabetic retinopathy. Through retinal photos taken by a camera called fundus camera, the ophthalmologists can diagnose which retina is at any stage of diabetic retinopathy, but this takes a lot of time because these diagnostic operations are done manually. [8]

Skin Images

Melanoma, one type of skin cancer is considered one of the most dangerous forms of skin cancer that occurred in humans. However, it is curable if the person detects it early. To minimize the diagnostic error caused by the complexity of visual interpretation and subjectivity, it is important to develop a technology for computerized image analysis.

Firstly, the image of the skin is pre-processed to remove unwanted hair and noise, and then the segmentation process is performed to extract the affected area. For detecting melanoma skin cancer, the watershed, EM and Unet algorithm that segments the lesion from the entire image is used in this study. Feature extraction is then performed by underlying ABCD dermatology rules. After extracting the features from the lesion, a feature selection algorithm has been used to get optimized features in order to feed for classification.

Figure 8 Hair removal preprocessing in skin image

Figure 9 Melanoma Segmentation after hair removal

tion stage. Those selected optimized features are classified using Ensemble Learning. The performance of the system was tested and compare those accuracies and get promising results.

Lung Images

Lung organ of human anatomy captured by a medical device reveals inhalation and exhalation information for treatment and monitoring. Given a large number of slices covering an area of the lung, we have a three-dimensional lung data. And then, by combining additionally with breath-hold measurements, we have fully lung data which is called 4DCT lung images. Up to now, it has still been a challenging problem to model a respiratory signal representing patients' breathing motion as well as simulating inhalation and exhalation process from 4DCT lung images because of its complexity.

The sequences of slices of Lung is put into LSTM to predict the state of exhalation or inhalation. And then the simulation of signal helps a doctor to diagnosis more accurately [9]

Breast Images

Breast cancer is the uncontrollable growth of malignant cells in the breasts. It's the most common cancer in women, although it can also develop in men.

The exact cause of breast cancer is unknown, but some women have a higher risk than others. This includes women with a personal or family history of breast cancer and women with certain

Figure 10 Left and Right Lung segmentation by Unets

TABLE 5. THE SUM OF LBP AND ENTROPY ERROR RATE REPRESENTS THE RESPIRATORY SIGNAL FOR SLIDES FROM 30 TO 70

Registration of Target Phase to the source Phase T00	Slices index	Sum of standard deviation of LBP and Entropy Error Rate	Remark
T10	Index from 30 to 70	0.1370	Start Inhalation
T20	Index from 30 to 70	0.3220	Inhalation
T30	Index from 30 to 70	0.4321	Inhalation
T40	Index from 30 to 70	0.5655	Inhalation
T50	Index from 30 to 70	0.7124	Start Exhalation
T60	Index from 30 to 70	0.6361	Exhalation
T70	Index from 30 to 70	0.4863	Exhalation
T80	Index from 30 to 70	0.4721	Exhalation
T90	Index from 30 to 70	0.1552	Finish

FIGURE 13. The demonstration of respiratory signal from phases T10 to T90 in registration to phase T00

Figure 11 LSTMs to predict the signal of inhalation and exhalation from lung slices

Figure 12 Breast Tumor Segmentation

gene mutations.

The tumor in breast is not easy in segmentation because there are a lot of region similar to tumor. For that case, the labeled image of breast is very important and then the position of detected region is also the key point to decide which candidate region is tumor or not. See in Fig. 12

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