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AN END-TO-END AUTOMATIC PANCREAS SEGMENTATION USING GENERATIVE ADVERSARIAL NETWORKS

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Abstract — Automated pancreas segmentation based on computed tomography (CT) is an effective method of computer-aided detection for the diagnosis of pancreatic cancer. The pancreas is a small soft organ present deep in the abdominal region of the body. Detection of the pancreas is very tedious in practice due to its high anatomical variability. The organ possesses varied shapes, orientations, and different aspect ratios. In this paper, we present a method to accurately segment the pancreas from abdominal CT using Deep Convolutional Generative Adversarial Networks (DCGAN).

Keywords— Generative adversarial networks, pancreas segmentation, Abdominal CT.

I. INTRODUCTION

Pancreatic cancer is the malignant abnormal growth of new cells in the pancreas. It is currently ranked as the 12th most common cancer in the world and 4th leading cause of cancer-related death [1]. It can be caused by DNA mutations that are inherited or it can form due to smoking, diabetes and consuming diets high in meat and cholesterol. As pancreatic cancer progresses, it can cause complications such as weight loss, jaundice, bowel obstruction, pain, and anemia. Nearly 90 percent of all pancreatic cancers found in people aged above 55 and men are more prone to pancreatic cancer than women. The incidence of pancreatic cancer in India is 0.5–2.4 per 100,000 men and 0.2–1.8 per 100,000 women.[2] Survival rates of pancreatic cancer are among the worst for any tumor, having the mortality to incidence ratio of 98 percent. Most cases of pancreatic cancer are diagnosed during the advanced stage of cancer. Due to this, most of the patients are not eligible for surgical treatment. Other treatments include chemotherapy and radiation therapy.

This study presents deep convolutional generative adversarial networks (DCGAN) and its application to pancreas segmentation on abdominal CT.

II. RELATED WORKS

In this section, a brief overview is given on previous research on pancreas segmentation and also similar segmentation methods for other organs. The first paper combines boundary maps and deeply-learned interior of organs through spatial aggregation using the Random forest algorithm. It generates boundary preserving class labels according to the pixels for pancreas segmentation [3]. In order to segment volumetric medical images, CNNs are used to obtain spatial information along all the axes. The paper achieves the latest state in terms of Dice-Coefficient [4]. The variable and complex background regions distort deep neural networks and then occupy a considerable portion of the input volume. Accurate segmentation is achieved by smaller input regions. The paper depicts the shrinking of the input region using a predicted segmentation mask. The average Dice-Sørensen Coefficient is 4% greater than other methods [5]. Segmentation of retinal fundus image is tough due to the variable size of vessels, relatively low contrast, and the presence of microaneurysms and hemorrhages. Data is pre-processed by normalization

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of global contrast, zero-phase whitening, and improved using gamma corrections and geometric transformations. A deep neural network is trained with this large data. This method outperforms the previous algorithms on the accuracy of classification and area under ROC curve [6]. An automated procedure for segmentation of White Matter lesion of Multiple Sclerosis patient images is performed using a cascade of two 3D patch-wise convolutional neural networks (CNN). The former network is trained to show the possible candidate lesion voxels while the latter is trained to decrease the misclassified voxels. The paper shows an increase in the segmentation accuracy of lesions when compared to other methods [7]. Segmentation of the liver and its lesions from CT scans is performed using Convolutional Neural Networks (CNNs) with a cascaded architecture. It first focuses on the region of the liver in order to segment the lesions on it. Further, a detector is trained to localize the lesions and mask the results of the segmentation network with positive detections [8]. Statistical models and multi-atlas label fusion (MALF) based segmentation methods require inter-subject image registrations which are difficult for abdominal images. A registration-free segmentation algorithm for eight organs such as pancreas, esophagus, stomach, duodenum, liver, spleen, left kidney, and gallbladder is proposed [9]. This paper presents a hybrid densely connected UNet for liver and tumor segmentation, with a 2D dense UNet for obtaining intra-slice features and a 3D counterpart for hierarchically aggregating volumetric contexts. The system outperformed other state-of-the-arts on the segmentation results of tumors [10]. Dense-Res-Inception Net (DRINet), consists of a densely connected convolutional block, a deconvolutional block with residual inception modules, and an unpooling block. DRINet outperforms U-Net in three applications [11]. SegNet is a fully convolutional neural network that performs semantic pixel-wise segmentation. The engine has a pixel-wise classification layer preceded by an encoder-decoder network. As compared to other architectures, SegNet performs well with competitive inference time and efficient inference memory. [12]

III. MODULE DESCRIPTION

A. Data collection

The dataset consists of 421 Portal Venous phase abdominal CT. The CT is sourced from Memorial Sloan Kettering Cancer Center and is a part of the Medical Segmentation Decathlon. The data is split into 282 training images and 140 test images. The training images also contain their corresponding binary masks.

B. Preprocessing

Image preprocessing is performed in order to improve or enhance the image and remove unwanted distortions like noise. It is a crucial step as it helps with further processes such as feature extractions.

1) Adaptive histogram equalization: Contrast-limited adaptive histogram equalization was performed using the adapthisteq function on MATLAB. The function works with small regions of the image. It enhances the contrast of each region. After performing the equalization, it combines neighboring regions using bilinear interpolation to remove artificially induced boundaries.

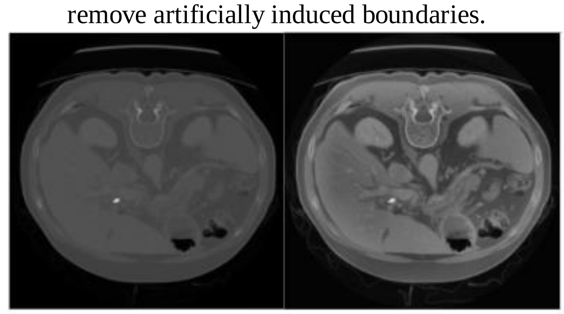

Fig 4.1 Original and Preprocessed image

2) Complexity reduction: Converting color images to grayscale reduces computation complexity. Color images contain more information than black and white images, and add unnecessary complexity and take up more space in memory.

3) Standardize images: Convolutional neural networks require all images in the dataset to be of a unified dimension. This implies that our images must be preprocessed and scaled to have identical widths and heights before fed to the learning algorithm.

C. Segmentation

This module performs segmentation of the pancreas from the abdominal CT using Generative adversarial networks. The segmented pancreas is depicted as a binary mask, where the pancreatic region is assigned a pixel value of 1 and the background is assigned a pixel value of 0. Segmentation using deep learning

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has achieved better performance as compared to traditional segmentation methods.

IV. METHODOLOGY

A. Proposed System

This paper proposes to segment the pancreas from the abdominal CT using Deep Convolutional Generative Adversarial Network (DCGAN). Generative Adversarial Networks entail two neural networks that compete with each other. The two neural networks are called the Generator and Discriminator. The Generator takes in random noise and maps it into an image such that the Discriminator cannot tell the generated image and original image apart. It maximizes the Discriminator's probability of making an error. The Discriminator finds the probability that the image is part of the original dataset and not generated. The Generator tries to maximize the Discriminator's loss and the Discriminator tries to minimize the Generator's reward. Generative adversarial networks work well with small datasets and provide better modeling of data distribution. Deep convolutional GANs (DCGAN) is a variant of conditional GAN. It has convolution layers without max pooling or fully connected layers. For upsampling and downsampling it uses convolutional stride and transposed convolution. It uses ReLU in the generator except for the output which uses tanh and LeakyReLU in the discriminator.DCGANs are more stable to train. In this paper, we have trained the DCGAN to generate abdominal CT images and their corresponding binary masks of the pancreas. The input to the network is abdominal CT images and ground truth labels. The outputs are the generated images and segmented pancreas structure.

B. System Architecture

The network consists of two blocks: generator, discriminator. The generator generates images and their corresponding masks and the discriminator classifies real images and masks from generated images and masks. The generator is given random noise as input and it generates the image and its annotation. The discriminator is then trained with the output of the generator (label 0) and the original image and mask (label 1). Once the discriminator is trained its weights are set and the discriminator block is stacked with the generator block. This stacked network is trained with the generated images with its label as 1. This training continues multiple times until the generated images are more meaningful. The generative and discriminative losses are plotted. The parameters of the network like the learning rate and optimizer are changed to improve performance. The generator and discriminator are set with Adam optimizer and a learning rate of 0.0002.

Fig 5.1 Generator Block

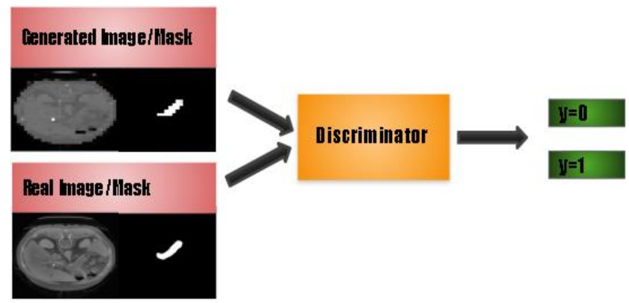

Fig 5.2 Discriminator Block

Fig 5.3 Stacked Network

V. RESULTS

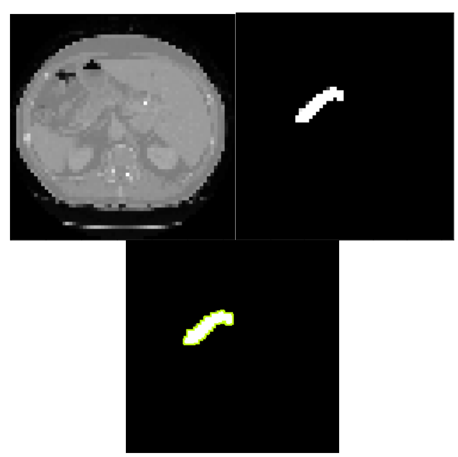

Fig 6.1 Generated CT, mask and mask with boundary

The pancreas have been segmented from abdominal CT using DCGANs. The generated images are quite similar to the original data and the discriminator has a classification accuracy of 52 percent. When it comes to applications in healthcare, accuracy is very important. The model should give 100 percent accuracy results. Even a small error in the model's prediction can have devastating impacts. Although this model performed satisfactorily, it has a lot of scope for improvement. The model shows an increase in generative loss over the epoch period, showing some instability. Even though the results generated by GANs can be remarkable, it can be challenging to train a stable model. The reason is that the training process is inherently unstable, resulting in the simultaneous dynamic training of two competing models. This means that improvements to one model come at the expense of the other model. One main challenge in this field is the lack of data and annotations. Medical image annotations have to be performed by clinical experts, and it's a costly and time-consuming job. In this paper, we have performed simultaneous generation of data and annotations using DCGANs. Considering the shortage of data and annotations in medical imaging tasks, the generated data and annotations using our method can be used for developing deep learning algorithms which require more data.

VI. FUTURE SCOPE

Advances in automated pancreas CT image interpretation are occurring at a rapid pace. In the near future, these advances may enable fully automated image interpretation. Such indistinguishable advances may occur in other body sections and with other imaging modalities. A huge flock of patients reside in countries with confined access to trained radiologists. Analysis using automation may be a more sustainable solution. It would provide accurate and quick detection from CT images and radiologists can further decide on treatment plans.

VII. CONCLUSION

The proposed method performs automatic segmentation of pancreas from continuous CT images, where the pancreas segmentation framework proposes to segment the pancreas from the abdominal CT using Deep Convolutional Generative Adversarial Network (DCGAN). In this project, we have used DCGAN to generate the CT image and its corresponding annotation or mask. GANs generate CT images thereby reducing the need for large amounts of data. The network outputs the binary mask of pancreas and the corresponding abdominal CT. Automated segmentation of pancreas can provide accurate diagnosis and reduce the misdiagnosis in cases. Automated organ segmentation and detection have a major role in medical imaging applications. One vital challenge in this field is the data and annotations insufficiency. Specifically, medical imaging interpretations have to be implemented by clinical experts, which is expensive and time taking. In this process, we introduce a method for the simultaneous data generation and annotations using GANs. Automated analysis may be a more sustainable and better solution.

VIII. REFERENCES

[1] Ferlay J, Steliarova-Foucher E, Lortet-Tieulent J, Rosso S, Coebergh JW, Comber H, *et al.(2012,2013)* Cancer incidence and mortality patterns in Europe: Estimates for 40 countries. Eur J Cancer; (49:1374-403).

[2] Dhir V, Mohandas KM. (1999)Epidemiology of digestive tract cancers in India IV. Gallbladder and pancreas. Indian J Gastroenterol;(18:24-8).

[3] H. R. Roth, L. Lu, A. Farag, A. Sohn, and R. M. Summers, (2016) "Spatial aggregation of holistically-nested networks for automated pancreas segmentation," in International Conference on Medical Image Computing and Computer-Assisted Intervention (MICCAI). Springer 2016 (pp. 451–459).

[4] Z. Zhu, Y. Xia, W. Shen, E. K. Fishman, and A. L. Yuille,(2017) "A 3d coarse-to-fine framework for automatic pancreas segmentation," arXiv preprint arXiv: (1712.00201).

[5] Y. Zhou, L. Xie, W. Shen, Y. Wang, E. K. Fishman, and A. L. Yuille, (2017) "A fixed-point model for pancreas segmentation in abdominal ct scans," in International Conference on Medical Image Computing and Computer- Assisted Intervention (MICCAI). Springer 2017 (pp. 693–701).

[6] P. Liskowski and K. Krawiec, (2016) "Segmenting retinal blood vessels with deep neural networks," vol. 35, no. 11. IEEE,(pp. 2369–2380).

[7] S. Valverde, M. Cabezas, E. Roura, S. Gonz´alez-Vill`a, D. Pareto, J. C. Vilanova, L. Ramio´-Torrenta`, A` . Rovira, A. Oliver, and X. Llado´, (2017) "Improving automated multiple sclerosis lesion segmentation with a cascaded 3d convolutional neural network approach," NeuroImage, vol. 155, (pp. 159–168).

[8] M. Bellver, K.-K. Maninis, J. Pont-Tuset, X. Gir´o-i Nieto, J. Torres, and L. Van Gool, (2017) "Detection-aided liver lesion segmentation using deep learning," arXiv preprint arXiv:(1711.11069).

[9] E. Gibson, F. Giganti, Y. Hu, E. Bonmati, S. Bandula, K. Gurusamy, B. Davidson, S. P. Pereira, M. J. Clarkson, and D. C. Barratt, (2018) "Automatic multi-organ segmentation on abdominal ct with dense v-networks," IEEE Transactions on Medical Imaging.

[10] X. Li, H. Chen, X. Qi, Q. Dou, C.-W. Fu, and P.-A. Heng, (2018) "H-denseunet: Hybrid densely connected unet for liver and tumor segmentation from ct volumes," IEEE Transactions on Medical Imaging.

[11] L. Chen, P. Bentley, K. Mori, K. Misawa, M. Fujiwara, and D. Rueckert, (2018) "Drinet for medical image segmentation," IEEE Transactions on Medical Imaging.

[12] V. Badrinarayanan, A. Kendall, and R. Cipolla, (2017), "Segnet: A deep convolutional encoder-decoder architecture for image segmentation," IEEE Transactions on Pattern Analysis and Machine Intelligence (TPAMI), vol. 39, no. 12, (pp. 2481–2495).