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DEEP LEARNING NEURAL NETWORKS IN LIVER SEGMENTATION

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Abstract -Liver cancer has been the second most fatal cancer to cause death for men and sixth for women. Early diagnosis by Computed Tomography could lead to high recovery rate, however going through all the CT slices for thousands or even millions of patient's manually by professionals is hard, tiresome, expensive, time-consuming and prone to errors. Therefore, we needed a reliable, simple and accurate method to automate this process. In this thesis we used 2D CNNs to overcome all the aforementioned obstacle, we used a Residual UNet model on the 3D-IRCADb01 dataset which contains CT slices for patients along with masks for liver, tumors and other body organs. Residual UNet is a hybrid between the U- Net and ResNet models where it uses Residual blocks rather than traditional convolution blocks. We used 2 Cascaded CNNs, one for segmenting the liver and extracting the ROI and the second one used the extracted ROI from the first CNN and segment the tumors. We achieved dice coefficient of up to 92% and True Value Accuracy of up to 97%.
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***Key Words*:**cancer, U-Net, CNN, ResNet, tumour, CT.

1. INTRODUCTION

. Automatic liver tumor segmentation would have a big impact on liver therapy planning procedures and follow-up assessment, thanks to standardization and incorporation of full volumetric information. In this work, we develop a fully automatic method for liver tumor segmentation in CT images based on a 2D fully convolutional neural network with an object-based postprocessing step. We describe our experiments on the LiTS challenge training data set and evaluate segmentation and detection performance. Our proposed design cascading two models working on voxel- and object-level allowed for a significant reduction of false positive findings by 85% when compared with the raw neural network output. In comparison with the human performance, our approach achieves a similar segmentation quality for detected tumors (mean Dice 0.69 vs. 0.72), but is inferior in the detection performance (recall 63% vs. 92%). Finally, we describe how we participated in the LiTS challenge and achieved state-of-the-art performance.

2. RELATED WORK

2.1 U-net

U-Net is a network that depends on the standard of completely convolutional systems [2]. It is made out of an encoder for extracting features and a decoder for remaking pictures. Also, skip association is used to join low-and elevated level features, empowering precise confinement. Such system design is regularly utilized for clinical picture investigation. Division of a 3D structure, for example, the liver, is performed by rehashing a succession of 2D slice segmentation. Since this approach does exclude the setting data along the z pivot, the consistency among slices is lost. Representation of U-net is shown in Fig-1.

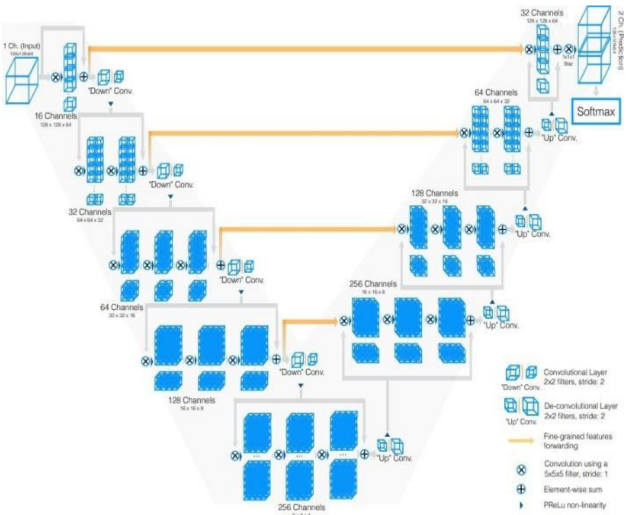

Figure -1: Schematic representation of the network architecture proposed by [1]

2.2 Residual U-net

ResNet resembles plain Artificial Neural Networks yet it acquains a little adjustment with simple architecture called Residual Blocks. Residual Blocks are the fundamental structure unit of ResNets and they use a significant idea called Skip Connections. The principle thought behind Skip Connections is to associate a layer with a successor layer of its successor layer Fig 2 .[5]

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Skipping layers streamline the system by utilizing less layer in the underlying preparing stages and furthermore quicken learning by lessening the impact of the Vanishing Gradient issue because of the way that there are less layers to proliferate through. Residual blocks reuse the activation function from previous layers to learn the weight and then adapts to amplify the skipped layer and mute the upstream layer.[5]

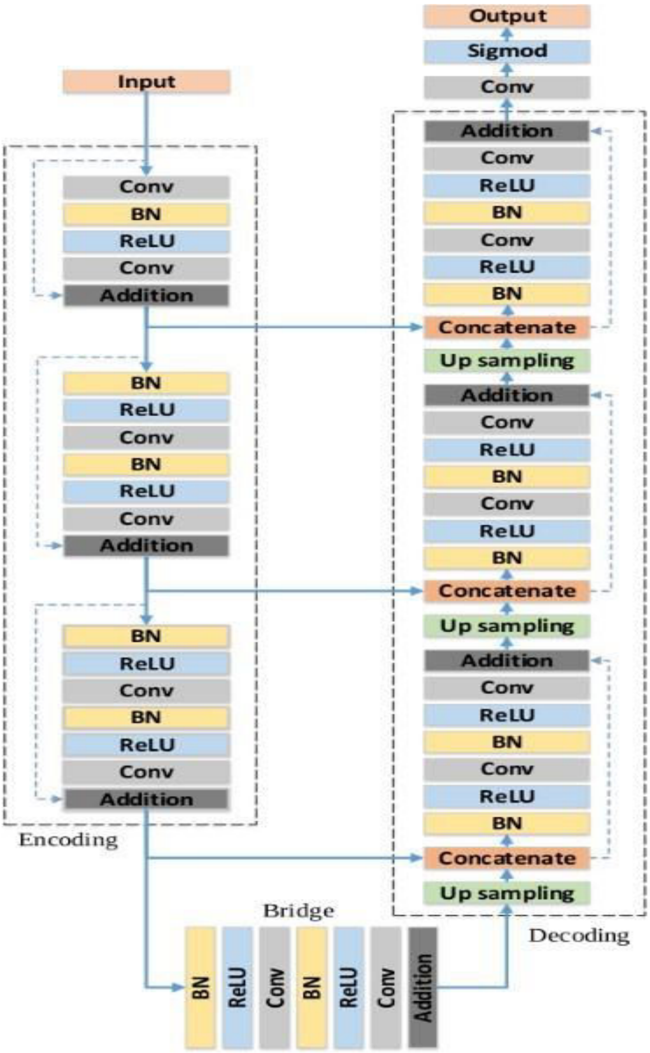

Figure -2: Detailed diagram of ResUnet Architecture

3. PROPOSED METHOD

Fig. 3 shows the flow of proposed work. Deep learning Model requires large number of datasets to give a result with acceptable accuracy. To increase the data .generally a technique or a process used is data augmentation wherein we can change the contrast, brightness to increase the data, but with that it increase the chance of overfitting problem which cannot be neglected. Overfitting is a situation where the training data get closely fit to the set of data points. Therefore to overcome the problem of overfitting, we can use GANs i.e. Generative Adversarial Network.Generative Adversarial Networks belong to the set of generative models. It means that they are able to produce / to generate new content. It comprises of 2 components i.e. generator and discriminator as we can see in Fig-2. The generative network generate content while discriminator network evaluate them.

Let us look in Fig-3, First of all split the data in two part i.e. training data and testing data. Testing data is kept untouched and will use later to check the accuracy of model. We Preprocess the data for better result, then for Data Augmentation we used GANs, then we used Resnet i.e. Residual U-net to extract feature of liver from CT scan, at this point we will have our reason of interest i.e. Segmented Liver, now we again used Resnet to extract feature of tumor .Initially we used U-net but to increase result further we used Resnet as it use skip connections to get better result.

Therefore initially worked with U-net and after getting a accuracy up to 72.34%, then worked with Resnet and achieve a accuracy up to 89%

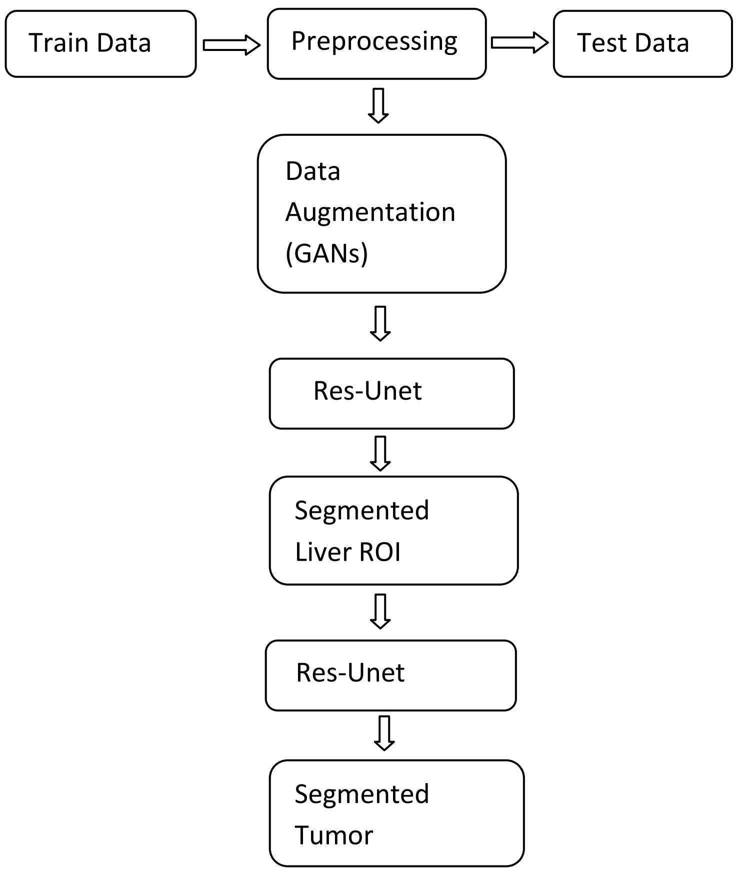

Figure -3: Proposed Model Flow

3.1 Generator

Generators used in GAN generate data by giving any random numbers. However, in the study, a liver segmentation image represents the output and a CT image represents the input. We used UNet as the network architecture of generator. Therefore a CT image is taken as input for a generator to generate similar image

3.2 Discriminator

Discriminator is used to evaluate the generated image produce by generator. If any generated image pass from discriminator that means that image is approved to be a part of dataset, and if it fails the image will get not be added in the dataset. Discriminator usually used to increase the accuracy of generated image from input data by GANs.

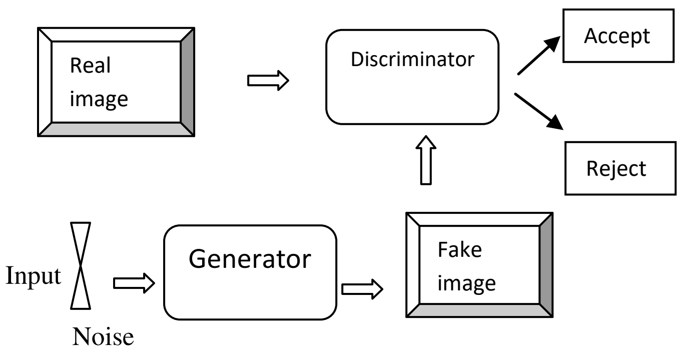

Figure -2: Workflow of GANs

3. CONCLUSIONS

This paper intent to give and establish a more accurate way to generate data apart from the normal augmentation i.e. to change brightness or contrast to increase data for training. GANs can actually generate a new yet similar from input data which can increase the data as well as the accuracy of the model. It also has a disadvantage that it need a good amount of hardware power to run. Yet there are many present application of GANs such as it can be used to create photos of imaginary fashion models, with no need to hire a model, photographer, makeup artist, or pay for a studio and transportation[7].it is also used in Video Games by recreating them in high resolution ,it is also used to improve astronomical images.

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