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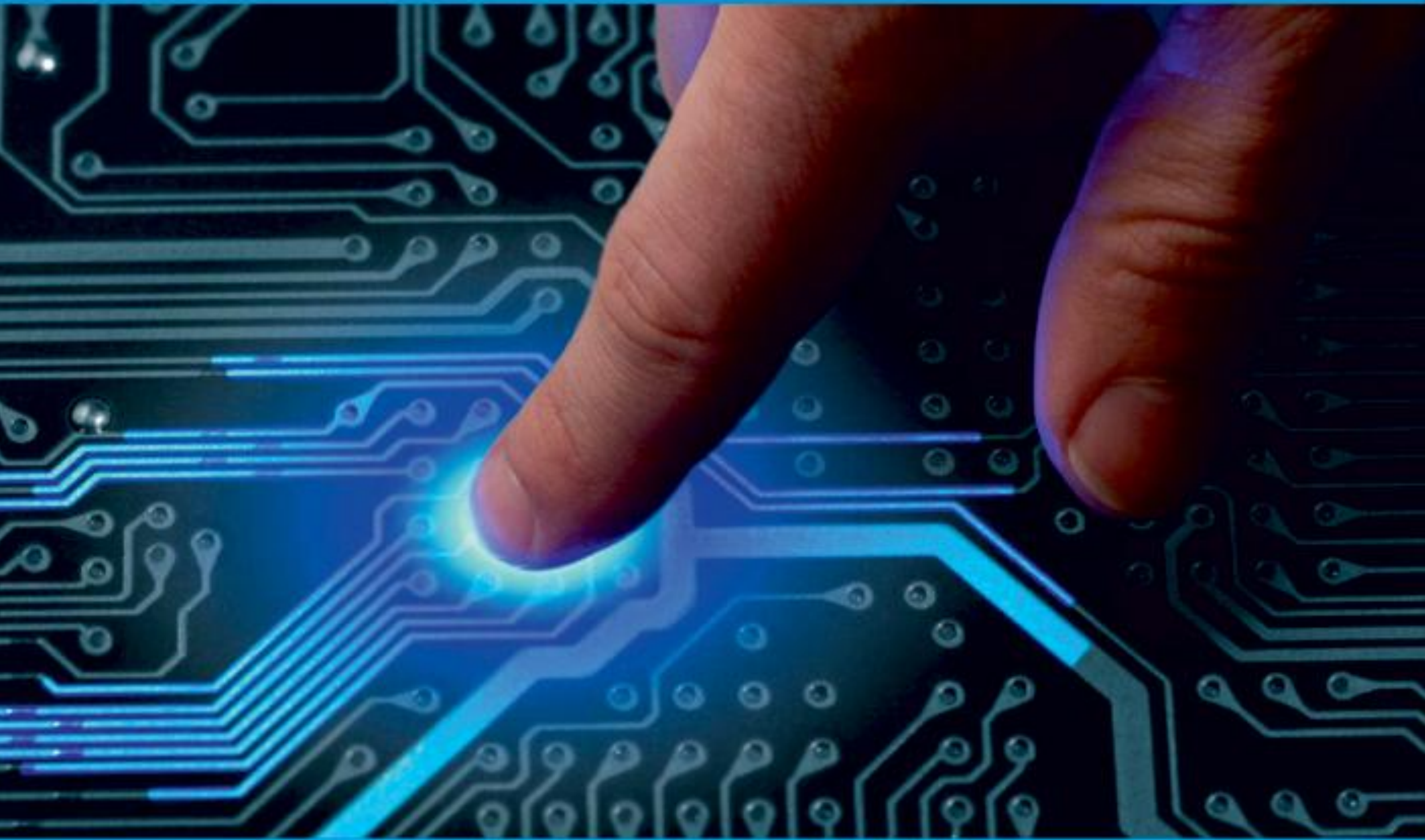

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Detection of Liver Cancer Using U-Net Architecture

Mohana sundaram K D[1], Vishnu Vardhan Reddy M[2], Sudha C K[3], Venkatesh B[4], Yashvanth kumar T[5], Vishnu Vardhan Reddy P[6]

Assistant Professor, Department of Electronics & Communication Engineering, Siddharth Institute of Engineering & Technology, Puttur, India[1]

Department of Electronics & Communication Engineering, Siddharth Institute of Engineering & Technology, Puttur, India[2,3,4,5,6]

ABSTRACT: Cancer is very dangerous disease that causes millions of death throughout the world. Various parts of human body can be affected with cancer cells. Liver cancer becomes very dangerous and it was found in most of the cases in recent days. It is very difficult to find liver cancer in initial stage. The recognition and segmentation of liver cancer from medical images is a major task. In this project, we propose a novel liver cancer image segmentation method based on Convolutional Neural Network (CNN). The main structure of a convolutional neural network adopts U-NET ('U' shaped network). U-NET is image segmentation. The network is based on the fully convolutional network and its architecture was modified and extended to work with fewer training images and to yield more precise segmentations. In order to capture objects of different scales in the deep features, a group of cascaded dilated convolution is inserted at the bottom of U-NET, which has different dilation rates. Furthermore, to better optimize the network at different scales, an auxiliary loss function is proposed to be integrated in the cascaded dilated convolution. We have proposed an effective and efficient hybrid architecture for extraction of liver cancer. Hence, liver diseases can be diagnosed using this technique and also be classified using the same using advanced computational techniques and large dataset. The system can match the results of a liver cancer thus improving the quality standards in the area of medicine and research.

KEYWORDS: CNN,U-NET, Deep Learning

I. INTRODUCTION

Liver cancer is cancer that begins in the cells of your liver. Your liver is a football-sized organ that sits in the upper right portion of your abdomen, beneath your diaphragm and above your stomach. Several types of cancer can form in the liver. The most common type of liver cancer is hepatocellular carcinoma, which begins in the main type of liver cell (hepatocyte). Other types of liver cancer, such as intrahepatic cholangiocarcinoma and hepatoblastoma, are much less common. Cancer that spreads to the liver is more common than cancer that begins in the liver cells. Cancer that begins in another area of the body — such as the colon, lung or breast — and then spreads to the liver is called metastatic cancer rather than liver cancer. This type of cancer is named after the organ in which it began — such as metastatic colon cancer to describe cancer that begins in the colon and spreads to the liver. Liver cancer is the sixth most common cancer worldwide. It is mostly diagnosed with a computed tomography scan. Nowadays deep learning methods have been used for the segmentation of the liver from the computed tomography (CT) scan images. This research mainly focused on segmenting liver from the abdominal CT scan images using a deep learning method and minimizing the effort and time used for a liver cancer diagnosis. The algorithm is based on the original U-Net architecture. But, here in this paper, the numbers of filters on each convolutional block were reduced and new batch normalization and a dropout layer were added after each convolutional block of the contracting path. Using this algorithm a dice score of 0.96, 0.74, and 0.63 were obtained for liver segmentation, from abdominal CT scan images respectively. The segmentation results of liver from the liver showed an improvement of 0.01 and 0.11 respectively from other works

As of the available literature regarding U-Net, the maximum dice score obtained for liver and tumor seg mentation is 0.9522 and 0.63 respectively. Additionally, Christ et all. Chlebus et al. had used 3D post processing methodsbettersegmentation results [8, 16]. But still, the segmentation performance was com paratively poor. In this paper, a deep learning-based segmentation al gorithm was employed for liver and tumor segmentation from abdominal CT scan images.

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The main contribu tions of this work are, first, it applied data augmentation tasks that solve the limitation of available data in bio medical images, second, it highly reduced the time needed for training by reducing the number of filters in each convolutional block thereby it reduced the number of trainable parameters and third it minimized the effect of class imbalance which presents between the tumor and the background through discarding slices with no tumor information from the datasets and used only slices with full information. These modifications improve the performance of the algorithm in detecting the tumor from the CT images. Finally, this work also showed the direct segmentation of liver tumors from the abdominal CT scan images without segmenting the liver first. By this, we were able to show the results of the three seg mentation experiments in one paper, unlike

ABC Algorithm

Automated and accurate classification of magnetic resonance (MR) brain images is a hot topic in the field of neuroimaging. Recently many different and innovative methods have been proposed to improve upon this technology. In this study, we presented a hybrid method based on forward neural network (FNN) to classify an MR brain image as normal or abnormal. The method first employed a discrete wavelet transform to extract features from images, and then applied the technique of principle component analysis (PCA) to reduce the size of the features. The reduced features were sent to an FNN, of which the parameters were optimized via an improved artificial bee colony (ABC) algorithm based on both fitness scaling and chaotic theory. We referred to the improved algorithm as scaled chaotic artificial bee colony (SCABC). Moreover, the K-fold stratified cross validation was employed to avoid over fitting

Finite Element Method

We have investigated the scattering of the Magnetic Resonance Imaging (MRI) radiofrequency (RF) field by implants for Deep Brain Stimulation (DBS) and the resultant heating of the tissue surrounding the DBS electrodes. The finite element method has been used to perform full 3-D realistic simulations. The near field has been computed for varying distances of the connecting portion of the lead from the air-tissue interface. Dissipated powers and induced temperature rise distributions have been obtained in the region surrounding the electrodes. It is shown that the near proximity of the air-tissue interface results in a reduction in the induced temperature rise.

Deep brain stimulation (DBS) is a well-established treatment for Parkinson's disease, essential tremor and dystonia. It has also been successfully applied to treat various other neurological and psychiatric conditions including depression and obsessive-compulsive disorder. Numerous computational models, mostly based on the Finite Element Method (FEM) approach have been suggested to investigate the biophysical mechanisms of electromagnetic wave-tissue interaction during DBS. In the present work we show that topological arrangements and geometrical properties of the model have a significant effect on the distribution of voltages in the concerned tissues.

Otsu's Method

Image enhancement is image pre-processing stage. The purpose of the process of image enhancement is to improve the image quality for the human eye. This process is also required to provide a better input image for further processing, so that the result of the image after processing all the stages contains less errors. The image enhancement technique is divided into two parts which are spatial domain technique and frequency domain technique. In spatial domain technique the value of the pixel is changed with respect to the requirement whereas the frequency domain technique deals with the rate of change of pixels which are changing due to spatial domain. It cannot be determined that what type of technique is good for image enhancement. There are many techniques for image enhancement technique out of which we have use Otsu's method.

Watershed Method

Marker-Controlled Watershed Segmentation process enhance the region which indicate the presence of the required object. The location which are extracted by this process are then set to the minimum position within the same topological surface. The watershed algorithm is applied afterwards. Separating objects of an image is one of the difficult methods which watershed segmentation makes it easier. Watershed Segmentation Approach is of two types: External associated with Background and Internal associated with the object of interest. Image feature extraction is one of the most important technique of image processing Watershed ridge and boundaries. It uses different techniques and algorithm to isolate and detect various shapes and portions of the image. The wavelet transform has a characteristic of analyzing the image with varying unit of resolution and has multi resolution analytic property. The wavelet transform is better than Fourier transform and short time Fourier transform as it preserves both time and frequency as in Fourier transform it discard the time. Different MRI Images where acquired from the internet, basic Otsu's preprocessing technique was used, for segmentation Marker-Controlled Watershed Segmentation was used and it was observed that for a few images' segmentation was done correctly.

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Prototype Passive Acoustic Brain Monitoring Method

An approach based on acoustics and its theoretical analogies to electromagnetism is used in the present research to study the detection of the acoustic wave energy radiated by the activation or caused by pathology. Pressure and particle velocity are calculated in analytical mathematical forms for the case of human brain monitoring, which can be implemented by a prototype passive acoustic brain monitoring system (PABMOS). A sphere to model the human head and an internal point source in order to simulate potential pressure alterations due to intracranial abnormalities or local functional activations, are used in the theoretical representation of the present approach. Finally, numerical results for arbitrary positions of the internal source, concerning the particle velocity (pressure field distribution) at the surface of the head model which can implicitly be measured by the suitable piezoelectric sensors, are presented.

II.EXISTING METHOD

A feed forward neural network is an artificial neural network wherein connections between the nodes do not form a cycle As such, it is different from recurrent neural networks. The feedforward neural network was the first and simplest type of artificial neural network devised. In this network, the information moves in only one direction, forward, from the input nodes, through the hidden nodes (if any) and to the output nodes. There are no cycles or loops in the network. The simplest kind of neural network is a single-layer perceptron network, which consists of a single layer of output nodes; the inputs are fed directly to the outputs via a series of weights. The sum of the products of the weights and the inputs is calculated in each node, and if the value is above some threshold (typically 0) the neuron fires and takes the activated value (typically 1); otherwise it takes the deactivated value (typically -1). Neurons with this kind of activation function are also called artificial neurons or linear threshold units. In the literature the term perceptron often refers to networks consisting of just one of these units. A similar neuron was described by Warren McCulloch and Walter Pitts in the 1940s. Single-layer perceptron’s are only capable of learning linearly separable patterns; in 1969 in a famous monograph entitled Perceptron’s, Marvin Minsk and Seymour Paper showed that it was impossible for a single-layer perceptron network to learn an XOR function (nonetheless, it was known that multi-layer perceptron’s are capable of producing any possible Boolean function). A single-layer neural network can compute a continuous output instead of a step function. A common choice is the so-called logistic function:

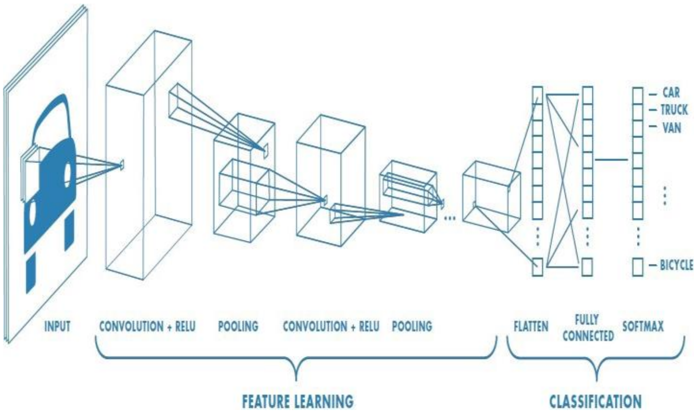
One also can use a series of independent neural networks moderated by some intermediary, a similar behavior that happens in brain. These neurons can perform separable and handle a large task, and the results can be finally combined.

III.PROPOSED U-NET METHOD

Artificial Intelligence has been witnessing a monumental growth in bridging the gap between the capabilities of humans and machines. Researchers and enthusiasts alike, work on numerous aspects of the field to make amazing things happen. One of many such areas is the domain of Computer Vision.

Convolutional Neural Network

The agenda for this field is to enable machines to view the world as humans do, perceive it in a similar manner and even use the knowledge for a multitude of tasks such as Image & Video recognition, Image Analysis & Classification, Media Recreation, Recommendation Systems, Natural Language Processing, etc. The advancements in Computer Vision with Deep Learning has been constructed and perfected with time, primarily over one particular algorithm — a Convolutional Neural Network.



Convolutional neural network

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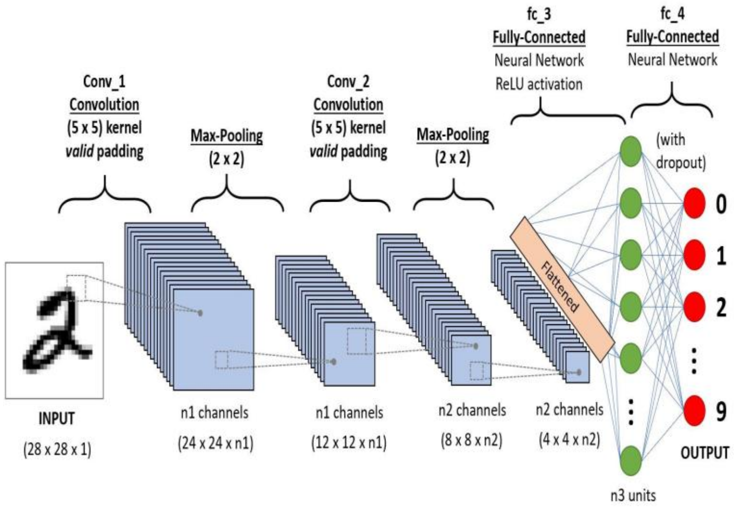
A Convolutional Neural Network (Convent/CNN) is a Deep Learning algorithm which can take in an input image, assign importance (learnable weights and biases) to various aspects/objects in the image and be able to differentiate one from the other. The pre-processing required in a ConvNet is much lower as compared to other classification algorithms. While in primitive methods filters are hand-engineered, with enough training, Convent's have the ability to learn these filters/characteristics.

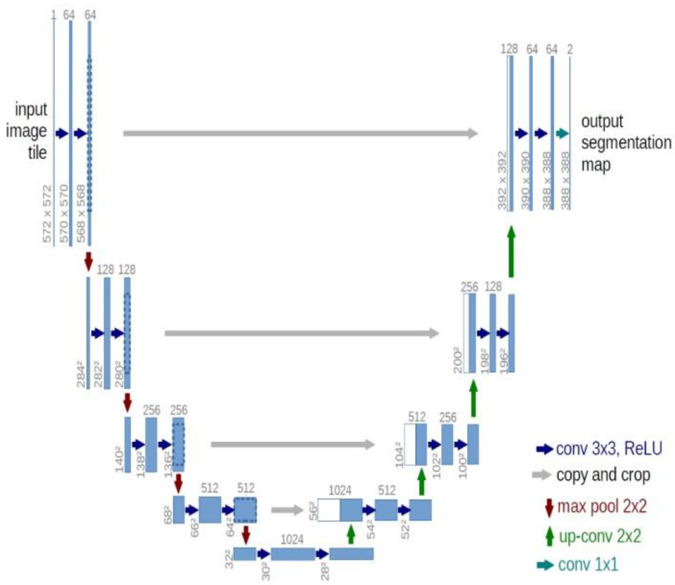


A CNN sequence to classify handwritten digits

The architecture of a ConvNet is analogous to that of the connectivity pattern of Neurons in the Human Brain and was inspired by the organization of the Visual Cortex. Individual neurons respond to stimuli only in a restricted region of the visual field known as the Receptive Field. A collection of such fields overlaps to cover the entire visual area.
A ConvNet is able to successfully capture the Spatial and Temporal dependencies in an image through the application of relevant filters. The architecture performs a better fitting to the image dataset due to the reduction in the number of parameters involved and reusability of weights. In other words, the network can be trained to understand the sophistication of the image better.

Differences That Make U-NET Special

As it's commonly known, the dimension reduction process in the height and width that we apply throughout the convolutional neural network—that is the pooling layer— is applied in the form of a dimension increase in the second half of the model.



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U-Net takes its name from the architecture, which when visualized, appears similar to the letter U, as shown in the Figure 4.15. Input images are obtained as a segmented output map. The most special aspect of the architecture in the second half. The network does not have a fullyconnected layer. Only the convolution layers are used. Each standard convolution process is activated by a ReLU activation function

IMAGE PROCESSING

Image segmentation objectives to split the desired foreground object from the historical past. Since coloration and texture in herbal pics are very complicated, automated segmentation of foreground objects from the complex heritage meets a vast impediment while foreground and history have similar functions. To cope with the problem, interactive image graph segmentation includes simple user interplay into image segmentation in a supervised or semi-supervised manner, and has acquired a lot interest in current years. Interactive image segmentation extracts foreground objects from the complex historical past by using taking gain of the consumer’s interactive enter. User interplay is employed to get prior information from customers which then play a critical role in guiding image segmentation. Thus, the project is to efficiently employ the constrained but treasured interactive inputs. In this painting, we attempt to maximize the guiding power of the given interactive statistics via propagating their characteristics through the whole image.

Digital Image Processing

Computerized image preparing is a range portrayed by the requirement for broad test work to build up the practicality of proposed answers for a given issue. A critical trademark hidden the plan of image preparing frameworks is the huge level of testing and experimentation that typically is required before touching base at a satisfactory arrangement. This trademark infers that the capacity to plan approaches and rapidly model hopeful arrangements by and large assumes a noteworthy part in diminishing the cost and time required to land at a suitable framework execution.

Reading Images Images are perused into the MATLAB condition utilizing capacity imread whose punctuation is Imread ('filename') Arrange name Description perceived expansion

TIFF Tagged Image File Format .tif, .tiff JPEG Joint Image graph Experts Group .jpg, .jpeg GIF Graphics Interchange Format .gif BMP Windows Bitmap .bmp PNG Portable Network Graphics .png XWD X Window Dump. xwd Here filename is a spring containing the total of the image document (counting any appropriate augmentation). For instance, the charge line

Image Type

The toolbox supports four types of images. A. Intensity images. B. Binary images. C. Indexed images. D.R G B images.

Most monochrome image processing operations are carried out using binary or intensity images, so our initial focus is on these two image types. Indexed and RGB color images.

Intensity Images

An intensity image is a facts matrix whose values had been scaled to symbolize intentions. When the elements of an intensity photo are of class unit8, or class unit 16, they've integer values within the variety [0,255] and [0, 65535], respectively. If the image is of class double, the values are floating point numbers. Values of scaled, double depth images are inside the variety [0, 1] by way of using conference.

Binary Images

Binary images have an extraordinarily precise meaning in MATLAB.A binary photo is a logical array 0s and1s.therefore, an array of 0s and 1s whose values are of statistics kind, say unit8, and isn't always viewed as a binary image in MATLAB. A numeric array is transformed to binary using characteristic logical. Hence, if A is a numeric array including 0s and 1s, we create an array B utilizing the declaration. B=logical (A) If A contains elements other than 0s and 1s. Use of the logical function converts all nonzero quantities to logical 1s and all entries with value 0 to logical 0s. Using relational and logical operators also creates logical arrays.

IV.RESULTS

Input Images

The original image of Liver without any preprocessing techniques applied. Image enhancement is the process of adjusting original image so that the resultant image is more suitable to display CT Images.

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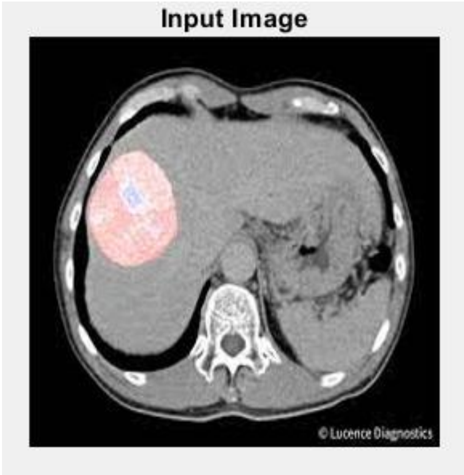
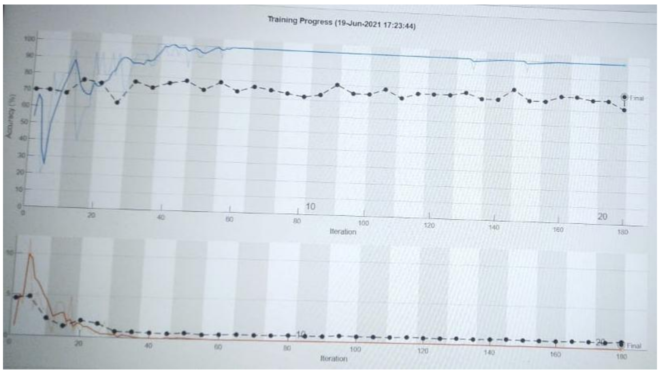


Input Image with Cancer cells

A Grayscale (Or Gray level) image is simply One (1) in which the only colours are only shades of gray. The reason for differentiating such images from any other sort of colour image is that less information needs to be provided for each pixel. It only contains the brightness information but not colour. A Grayscale image is one with all information removed. Here we are using grayscale image as an input image because the colour increases complexity of the model. So, the inherent complexity of gray level images is lower than that of colour images

Iterations

The Figure 7.2 shows the Iterations that are used to train the Input Images in CNN (Convolution neural networks). In this process 10 iterations are used to train the image. The above training progress the first plot shows the accuracy of the trained input image which is including in the both training and validation of that particular image



Segmented Images

The input gray scale image is segmented using the U-Net architecture if the input image contains Tumour in it. If the input gray scale image does not contain Tumour the segmentation process is not required. The Figure 7.8 shows the final segmented image of an input image containing Tumour in it. The final segmented image differentiates the Tumour part of the image with the rest of the image

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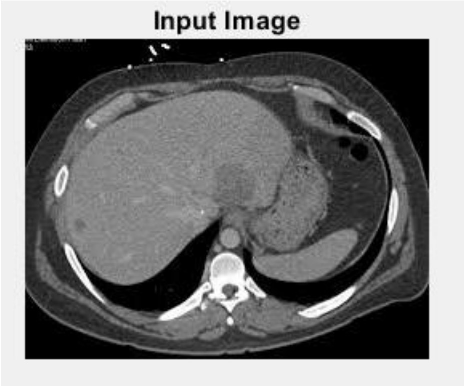

Input without cancer

V.CONCLUSION

Incident rates of hepatocellular carcinoma liver cancer have been rising since last two decades. So, effective and fast detection of liver cancer is paramount importance. If detected in the early stage, it can be cured in most of the cases, the treatment is also simple. we have proposed an effective and efficient hybrid architecture for extraction of liver and tumor from CT volumes. n. The proposed network takes advantage of the strengths from the U-Net, the residual learning, and the attention residual mechanism. Firstly, attention-aware features change adaptively with the use of attention modules. Secondly, the residual blocks are stacked into our architecture which allows the architecture to go deeply and solve the gradient vanishing problem. Finally, the U-Net is used to capture multi-scale attention information and integrate low-level features with high-level features. It indicates that our method achieved competitive results in liver tumor challenge. Thus, we have learned about Convolutional Neural Networks and how it is used for image classification

VI.FUTURE SCOPE

A more refined approach would be to leverage a network pre-trained on a large dataset. Such a network would have already learned features that are useful for most computer vision problems, and leveraging such features would allow us to reach a better accuracy than any method that would only rely on the available data. We will use the VGG16 architecture, pre-trained on the ImageNet dataset --a model previously featured on this blog. Because the ImageNet dataset contains several "cat" classes (persian cat, siamese cat...) and many "dog" classes among its total of 1000 classes, this model will already have learned features that are relevant to our classification problem. In fact, it is possible that merely recording the softmax predictions of the model over our data rather than the bottleneck features would be enough to solve our dogs vs. cats classification problem extremely well. However, the method we present here is more likely to generalize well to a broader range of problems, including problems featuring classes absent from ImageNet.

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