SEGMENTATION AND PREDICTION FROM CT IMAGES FOR DETECTING LUNG CANCER

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***Abstract*—Cancer is one of the most usual medical condition across the world. There are numerous types of cancer and lung cancer happens to be the most usual one amongst the population. Lung cancer affects people irrespective of their gender and is one of the most fatal medical condition in the world. Identifying cancer at an early stage is a vital step that aids in minimizing the risk of death. In this paper, the CT scan data set of the lungs obtained from Kaggle and LUNA (Lung Nodule Analysis) websites has been implemented to perform classification of lung nodules. In recent years, Deep learning and machine learning algorithms have been sought after to perform classification of lung nodules. In this paper, UNET architecture of CNN model is implemented. From the Deep Learning library, machine learning and deep learning algorithms happen to be the most employed for the implementation of 3D Convolution Neural Networks and TensorFlow.**

***Keywords*— Cancer Detection, Feature extraction, Image processing, Lung segmentation, Dilation, Erosion, UNET Architecture.**

I. INTRODUCTION

In the past years, approximately 1,372,910 new cancer cases are predictable and about 570,280 cancer deaths are expected to occur. It is expected that there will be 163,510 deaths from lung cancer, which forms 29% of all cancer deaths. When cells start to grow out of control, cancer begins in a part of the body. The cancer cell starts because of out of control expansion of abnormal cells.

For machines the most complicated obstacle happens to be applications which involve sight and hearing. Unlike humans, for machines both the mentioned senses do not come naturally. But thanks to Deep learning and machine learning, the solutions to these limitations posed by machines are being implemented in a smooth and efficient manner and is only improving with every passing day. The invention of Artificial Neural Networks has been the biggest leap in the field of deep learning and machine learning. ANN, CNN and machine learning has been around for a while now, but only in theory and very rarely it has seen practical applications. One of the biggest challenges faced is that the technology has not been able to meet the demands and requirements of these algorithms in terms of processing power. But multiple layered structures have emerged (Deep learning) in today's era of fast paced growth of advanced technology.

In recent years, Deep learning techniques have been the most sough-after. There are many obstacles and challenges faced in the domain of image processing, signal processing and natural language processing and the go to solution to all these challenges has been the algorithms that come under 'Deep Learning'.

One domain where deep learning techniques have been the most sough-after is in the field of Biomedical Image Classification. There are numerous methods employed to identify ailments and for this purpose the most favoured preliminary step would be to have a look at Computed Tomography images.

II. LITERATURE SURVEY

Qiu, Gnoping, et al.[1] focusses on an improved recursive median filtering scheme for image processing. Images may be corrupted with pseudorandom, salt and pepper noise, Median filter happens to be the go to application that is implemented to reduce such noises that occur in an image. This paper recorded that the recursive median filter method provides better performance giving a MSE value reduced by 15.3%.

Alam, et al.[2] focusses on marker-controlled water shed algorithm. The first step of the approach involved pre-processing the image with techniques such as applying a median and bilateral filter. The second step, it checked if the lung has been diagnosed with cancer or not, if a cancer cell or a nodule is detected, the algorithm classified. The first, second, third or the final stage. For prediction a total of 200 images were taken into consideration and it predicted with an accuracy of 87% (174 images). For detection, out of 100 images, it predicted that 3 lungs have cancer and the other 97 to be non-cancerous with an overall accuracy of 97%.

Christian Bauer, et al. [3] focusses on 'Region Growing Algorithm' & 'Template Based Segmentation Approach'. 30 data sets, 40 cancerous lungs, 20 perfectly healthy lungs were evaluated to produce a result of 4mm in terms of MASDR (Mean Absolute Surface Distance Error).

Reinhard Beichel**,** et al.[4] focusses on the first approach is the 'Random Forest' approach while the second approach being 'Support Vector Machine' classification. With an efficiency of 94.5% the Support Vector Machine classifier proved to produce the best results.

Rishi Gupta, et al. [5] focusses on implementing an automated, efficient, smooth and a human error free model with the help of ANN model (Artificial Neural Network Model). An efficiency of 78% was obtained after running for 25 epochs with an MSR of 0.1 in the validation.

III. MOTIVATION

The proposed work was done with the implementation of CNN model UNET Architecture, that hasn't been implemented for early detection of Lung Cancer in any of the following research papers till date. This contains Convolutional layers and does not contain any Dense layer because of which it can accept image of any size. Up-sampling provides contextual information of the image whereas Down-sampling provides location information.

Conventional methods are tedious, time consuming, prone to human errors and these manual delineations leads to inconsistency and bias, Implementation of this model we look to negate and improve the entire process of lung cancer detection.

IV. DICOM IMAGES

The proposed work focusses on collection of data set, segmentation and prediction of cancer cells present in the lungs. The data set mainly consists of CT scan reports for 1600 patients. The complete data has been taken from two different sources which are Kaggle website and from the lung nodule analysis mainly known as luna. There is a file called DICOM which means digital image communications in the medical domain.

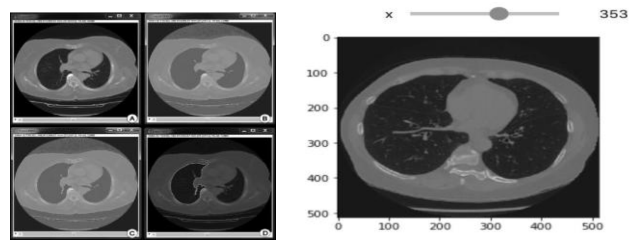

Fig 1. DICOM Images of Lungs

All the DICOM files which are present, in that every person has his own DICOM file, it can be identified only with the help of a parameter called meta data which is mainly available in the DICOM file. The meta data is nothing but a unique ID which is given to every patient. This DICOM file mainly comprises of many slices of the entire chest region of that particular patient. All the slices which are present in the DICOM files are located at various geographic and geometric locations over spatial region and each slice is a 2D image, later from a 2D image it can be combined to form a 3D image of the entire chest region.

DICOM Standard

DICOM is an acronym for Digital Imaging Communications in Medicine. Files in this for format are either stored with the extension DCM or DCM30 file extension, however some won't have an extension at all. It is used for both conversation protocol and a file layout conversation protocol. All the patient's medical history, all their ultrasound scans, and the MRI photos are all clubbed into one file. This is done mainly so that the complete data can be transferred very easily between various devices where the DICOM format is supportable. There are two methods in which the files can be viewed which are:

1) With the help of RadiAnt FreeViewer
2) With the help of PyDicom.

Opening DICOM files with RadiAnt free viewer

A file viewer named radiant is used which is an open source software mainly for seeing the DICOM files. The meta data which is present with the image helps in making it smooth and can give access to the data. DICOM has its very own standard, even though there are many open source softwares and many open libraries, the package used here is PyDicom, this package is mainly used for making it work with the images in python.

V. METHODOLOGY

The process involves multiple steps right from collecting the data set to processing it and performing several steps in order to obtain the required result.

BLOCK DIAGRAM

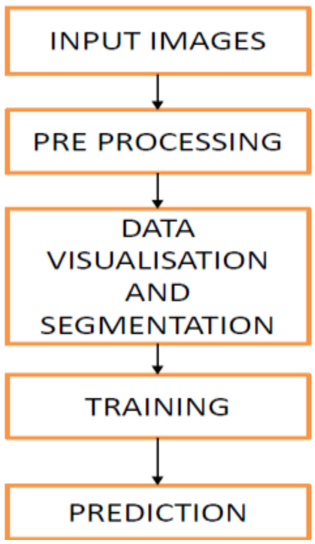

Fig 2. Proposed Methodology

Pre-Processing

Image pre-processing: Image pre-processing refers to performing mathematical operations with images at the basic level There are some image pre-processing techniques like Enhancing the image, Resizing the image, Increasing the contrast, Blurring the image, Sharpening the image, Isolating colours, Binarizing the image, and many more. Let us consider only useful pre-processing techniques that are related to this project: The data-set incorporating RadiAnt DICOM to perform examination about the statistics. The patient id call provided for every affected person in each scan in the folder. Taking more metadata tags into consideration finding anomalies which might be the root cause for pre-processing.

The steps involved, reducing pixel size and depth to process data, Sampling list of slices into chunks of list, limiting each patient CT Scan to 20 slices, To process CT scans and save them as dimensional array for neural network and Saving the processed data as list.

Data Visualisation

Data visualization is the graphical representation of information and data. data visualization tools provide an accessible way to see and understand trends, outliers, and patterns in data. Effective data visualization is a delicate balancing act between form and function. Modules include NumPy, Pandas, Pydicom, SciPy, matplotlib. Steps involved in the process of Data-Visualisation, Uploading the scans in the given folder path, converting to Hounsfield Units (HU), Combining 2D slices placed at different geometric locations to form a 3D image. Use of matplotlib enabled to plot a graph of ‘frequency against Hounsfield Unit’ for a particular patient’s CT Scan image of the lung. Further step of data visualisation involved compiling the different 2D slices of a patient’s CT scan image placed at different geometric locations to form one 3D lung image.

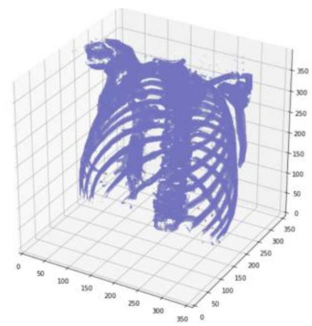
Fig 3 3D Image of the Chest

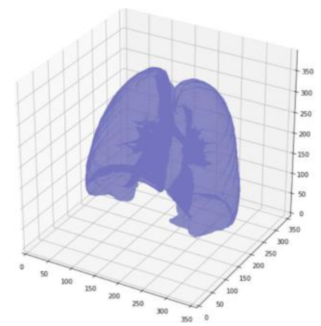
Fig 4 Segmented Lung Region

Lung Segmentation

This is an essential step in analysing images and extracting data. Using this method, one can obtain the region of interest from the existing image. Then, further analysis like feature extraction can be performed on it to obtain the features. Before we go further with pre-processing it is important to eliminate those portions of the chest region that are not required and only retain the segmented portion of the lung region. This has two advantages, Firstly, Reduces time and space complexity. Secondly, Improves the efficiency of the model.
Since we know that the region around the lung is filled with air, a pixel around the lung Region labelled as ‘Air’. Filling the lung structures with morphological closing operation. Morphological closing is a process where dilation is followed by erosion. For every slice we determined the largest structure and this largest structure labelled to be a portion of the lung. Finally, all the scanned structures put together to form the lung region. This image converted into a binary image. The air packets removed from the lung region.

In Dilation the boundaries of objects in binary image is added with pixels to give it the perception of thickening or growth. The number of pixels that are to be added depend on the size and shape of the SE (Structuring Element). This SE is moved across the image from left to right and from the top to bottom. Every time the structuring element overlaps with the pixel of an object in the binary image, it is called a hit and a pixel gets added around the pixel which has been just overlapped by the structuring element. This gives the perception of growth to an object in the binary image.

In Erosion an object in the binary image sets the perception of shrinking after certain number of pixels have been eliminated around the boundary based on the size of the structuring element. This structuring element is parsed from left to right and from top to bottom and every time there is a hit, the pixel of the object gets eliminated.

VI. 3D CNN – UNET ARCHITECTURE

Convolutional Neural Networks: Another machine learning approach we used to classify is Convolutional neural networks. With more data to work with, and higher computational speed, CNN's gained traction. In recent times, Convolutional neural networks have been proven very effective in the areas of image recognition and classification. Unlike other algorithms, where input is in the form of a vector, CNN can directly take an image as an input. The main advantage of this is that hand engineering of features is no longer required, as CNN has the ability to learn features on its own. To get more intuition on how this happens, we'll look at different layers and working of the CNN model. This section mainly comprises of the steps, which are required for pre-processing the data and the data which is obtained after pre-processing is used for the prediction. In this case the prediction is to tell whether a person will be suffered from cancer or not and the pre-processed data also helps in giving the accuracy of the model.

Different layers of CNN include-Convolution layer: It is the first layer of a CNN. As discussed above the CNN model takes an image as an input. As the name suggests, the convolution operation is performed in this layer. To perform a convolution operation there are two inputs given to it, which are:

Firstly, an input image which should have a 3D volume and it should comprise a respective size of channels. Secondly, There are some set of kernels present basically known as k filters and each one of them should comprise a size of f x f channels, where the value of the f can be either 3 or 5. The output image which is obtained from the convolution operation, the output image is also a 3D volume which is same as the input image and it should comprise a size respectively. The connection between respective size is as described in (1).

$$N_{out}=[(N_{in}+2p-k)/s]+1 \qquad (1)$$

Pooling layer: The convolutional layer is usually followed by a pooling layer. Decreasing the spatial size of the convolved feature is the primary objective of the pooling layer. When the spatial size is reduced, it takes computationally less power to process the data. This is helpful when we are dealing with high dimensional data or when we are dealing with large datasets.

UNET Architecture

The UNET model, mainly developed for the segmentation of the bio medical images. The architecture which is present in UNET mainly consists of two paths. The first path in the architecture is the path contraction which is also known as the encoder. This is mainly used to reduce the context which is present in the image. The encoder has a combination of two different layers which are the convolutional layer and the max pooling layer. The second part in the architecture is expanding its path symmetrically which is also known as decoder, with the help of the transposed convolutions it enables the usage of certain specific locations. So therefore it is a fully convolutional network. It only uses convolutional layers and dense layers are not being used so that it can accept any image of its own size.

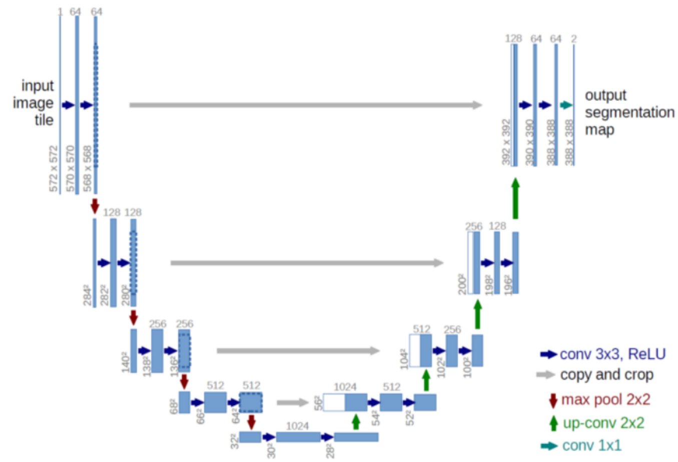

Fig 5. UNET CNN Model

Up-sampling

As mentioned previously, the output which comes from the semantic segmentation it's just not a class label or the parameters which are in the boundary. The output which has been obtained from the semantic segmentation is completely a high-resolution image in which all the pixels of that particular image can be classified. So if we use a general convolution neural network which consists of two different layers which are the pooling layers and the dense layers, if this is being used then we will completely loose the where data and we just remain with what data, which is not at all required in this process. When segmentation comes into picture, we need to have both the what data as well as the where data. Hence a sampling needs to be done on the image, i.e. to recover the lost where data the image should now be converted from a low-resolution image to a high-resolution image with the help of up-sampling method.

Transported Convolution

Sometimes the transported convolution is also referred to as deconvolution or even fractionally stride convolution. This transported convolution is a method for sampling the image with the parameters. As the level keeps increasing then the transported convolution becomes less effective and then the regular convolution comes into the picture i.e. if the resolution of the image is high in the output quality and it has a low-resolution picture in the input volume. The complete system can just be reversed by just taking the transpose of the filter matrix.

VII.RESULTS

Training

The inputs were given in the form of 3D images, which were being pre-processed. There is no fixed rule that the values do not remain the same at all the point of time. So, for getting the certain value there are multiple tests which have to be done frequently so that a particular value can be obtained and the value stays on the top. So, when a model is being trained the information is automatically being split so that only a part of the information is used for training the model and the remaining information is just preserved for the testing process no matter even if the model is trained or not. We have almost trained the model with 1600 images and saved around hundred images for the testing purpose. The main idea here is to complete the training of the model with 1495 images and pass the next 100 testing images to check how much accuracy is shown in the results. To be more precise we are just giving the testing data as the input to the trained model to just check the accuracy. The range is being set for the batch size so that the epochs can run, and whenever input data is given it specifies that how many images have to be processed at only once. The dimensions of the input size are also restricted to 50x50x20 but the machines which we are training can only adjust itself to certain capacity. So, because of this reason the data sets quality and quantity has been completely reduced. when the model ran for 100 epochs, we had made an observation that the accuracy of the model remained same at that 83rd epoch and we have obtained an accuracy of 70%, which has been maximum accuracy so far for this model. Before finding the final accuracy of the model we had tried mix and match between some of the layers so that the accurate composition could be obtained. To be more precise first we had set three layers and executed it we have got an accuracy of 54% with just 3 runs of epochs and we have observed that the accuracy has been improved. We saved the previously used layers and extended that to six layers which has become very much efficient and it just changed the epochs into high quality so that maximum accuracy can be obtained.

Result

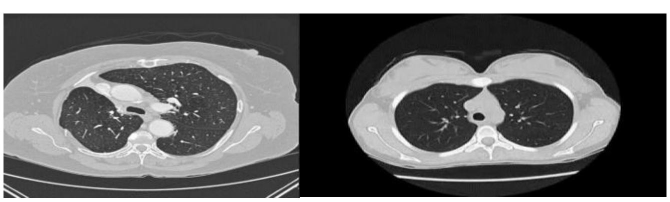

Fig 6.a. Cancer Patient's Image
Fig 6.b. Non-Cancer Patient's image

The below table depicts the accuracy of the Model classifier when tested with mix and match between some of the layers so that the accurate composition could be obtained. When tested with CNN, an accuracy of 70% was achieved.

Epoch	Loss:	Success rate:	Accuracy:
Epoch 1	20867480832.0	1.0	0.46
Epoch 2	36023595008.0	1.0	0.55
Epoch 3	51028041728.0	1.0	0.54
Epoch 4	23555268608.0	1.0	0.63
Epoch 5	26307223808.0	1.0	0.67
Epoch 6	27548338529.0	1.0	0.65
Epoch 7	53289402392.0	1.0	0.70
Epoch 8	23393960326.0	1.0	0.68
Epoch 9	42259205205.0	1.0	0.63
Epoch 10	45828402949.0	1.0	0.69

Table.1 Accuracy reports of each epoch

CONCLUSION AND FUTURE WORK

We were successfully able to train data set into UNET model segment and predict the presence of cancer cells in lungs. Over the course of the project, During the first phase, we learnt the various pre-processing techniques that we could apply to an image such as mean filter, median filter, gaussian and the bilateral filter. This project presented us an opportunity to work with 3D Images (DICOM files) with the help of a package called the 'PyDicom'. We learnt how to work with huge volumes of data by employing TensorFlow. Error handling is another major skill that we have developed throughout the course of the project which will help us in handling errors in a much quicker and efficient manner and also prevent them from even happening. Since we had the opportunity to apply the above-mentioned concepts onto a real-life problem, it gave us a better and deeper understanding.

However, the proposed does not classify into different stages of cancer, could be able to do only binary classification Also, further accuracy can be increased by including real time data and elimination of false objects.

In this project, that we have taken is only at the very beginning of its development stage and we desire to carry this project ahead mainly because we believe that much greater improvement can be made to this project by employing Microsoft's ResNets. The advantages of using Microsoft's ResNets are, it makes more valuable predictions, achieves a much higher value of accuracy, provides a higher learning rate, Minimizes the losses. We would wish to carry out this project with the Resnets approach and take this project to the next phase, i.e., the application stage and try and make an impact to the medical industry, contributing in the way we can and have an impact on the life of the individuals.

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