Increasing the Efficiency of Lung Cancer Detection by Improving Local Magnification Operations of the FPR Network

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Abstract: Lately, lung cancer has become a terminal disease increasing the mortality rate due to the late diagnosis of the ailment. Early diagnosis can help reduce the death rate abundantly. The prediction of abnormalities from the given input images is a crucial factor. Deep learning has played an important role in early cancer detection by training networks to detect abnormalities via the given image. Convolution Neural Network (CNN) are most commonly used for cancer detection. In this paper, we propose a CNN with the concept of down-sample in the Region of Interest (RoI) of the Computed Tomography (CT) images where the RoI will be subjected to magnification. Here, the magnification operation will first identify a spot from the upper region and then travel downwards towards the end of the CT image. However, every RoI will undergo local magnification process before the network could detect the next lesion. Detecting lesion are more effective as the lesions are disrupted structures in the human tissues that projects anomalies in the section viewed. Therefore, these anomalies can be useful in detecting lung cancer efficiently.

Keywords - Lung cancer, Deep learning, Down-sampling, Local Magnification, Lesions

I. INTRODUCTION

Today, cancer is considered as a disastrous ailment that has increased the death rates across the globe. This terminal disease has alarmingly spread in the recent years as a result of change in the lifestyle of the people. In [10], initially poverty was directly proportional to the mortality rate of cancer. The ability of the people to afford for the treatment had a toil on their survival rates. Eventually more and more victims of cancer were identified amongst which the occurrence of lung cancer was high. A

study in [4] mentions that though the treatment is advanced, the recurrence of cancer still prevails. In

addition, the late diagnosis also added to the increased death rates. However, with development of technology, diagnosis and treatment of cancer has become inexpensive to the people. The growth of economy and technology has facilitated the decrease in the death rates.

Amongst technology, deep learning has created a stronghold in the field of cancer detection [3]. Early cancer detection can help treat cancer patients and increase the survival rate of the victims.

Deep learning uses neural networks to classify input images to predict if the concerned person is affected by cancer or not [9].

Most medical imaging models use deep learning for prediction and analysis.

In [12], deep learning is associated with the in-depth analysis of input images rather than the layers. The main objective of deep learning is to learn the model to a wide extent. These networks extract features across layers to predict cancer accurately. Numerous data is used to train the model that makes the model more efficient and diversified. The variety of images fed into the network allows the model to detect abnormalities that facilitate early diagnosis [1]. Recently, convolution neural network has been widely used for lesion detection in the lungs. The main source for lung lesions are Computed Tomography (CT) scans that project spot like structures called Lesions. These lesions help in identifying abnormalities in the CT images which help in classifying cancerous images. However, lack of local magnification of the CT images may influence the accuracy of the predicted value. Therefore, improving the local magnification operations may further make the diagnosis of cancer more efficient. We will propose an improved local magnification operation that will enhance cancer detection in CNN at a faster pace. Also, the drawbacks in the existing model and the literature gap will be highlighted.

II. RELATED WORK

In [5], image magnification is a critical attribute of image processing that helps in detection and feature extraction. Image processing being the essential factor in lung cancer detection, magnification becomes crucial for predicting abnormalities in the given input images. In [8], they use the concept of 'up-sample Region of Interest (RoI) crops' in order to reduce the memory occupied and simultaneously zoom-in to the region
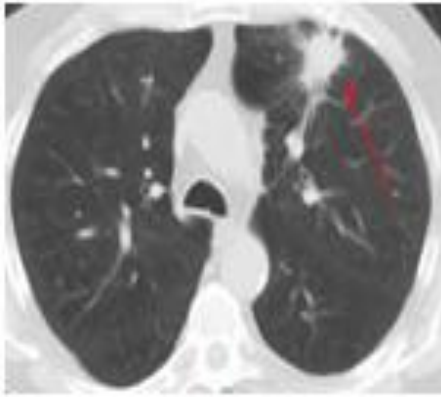
Fig. 1: An up-sample approach where the network chooses the RoI in the upward direction starting from the lower region passing over every lesion possible.

Fig. 2: The picture shows the enlarged local section of the lesion selected depicting localisation of the corresponding RoI

This works in such a way that the RoI is sectionally cropped and the lesion is spotted over a small area.

Then the enlargement of the spot takes place thereby magnifying the RoI to identify the anomaly. Therefore, the Convolution Neural Network is fed with multiple CT images with variations to train the network to detect the lesions. The model considered a 3D CNN network for the generalised detection of lung cancer in the given input image. Here, a False Positive Reduction(FPR) value is used to reduce the focal loss in the prediction process. The network traverses from the upper direction to spot the lesion and magnify them with a minimal focal loss value. This has been tremendously effective in identify lung cancer at a much earlier stages. However, the usage a FPR has influenced the accuracy of the prediction [11]. The lower region might be misleading as the lung lining looks similar to the lesions and may be deceptive to the network fed. Therefore, the diagnosis may be less effective. This calls for further research in the area of local magnification operations of the CNN. This paper will propose a down-sample approach that will make the diagnosis more effective.

III. PROPOSED WORK

This paper highlights the effects of down-sampling in the CT images that facilitate local magnification by cropping the images. In [2], magnification in traditional models are based on the feature extraction outcomes. The network brings out all possible features that it has learnt to extract while training. The extent of magnification defines the accuracy of the models. Existing techniques view the images in the upward direction. This method allows the network to magnify the anomalies that comes in contact first. As a result, the lung lining will be viewed by the model first and chances of predicting the lining as abnormal is high. Additionally, using a FPR may also increase the inaccuracy. Therefore, we propose a concept called 'down-sample' that will view the given image in the downward direction with a specified padding measurements. Padding allows the model to view the input image within the mentioned area. This way the model will first scan the entire image and then traverse in the downward direction to detect anomalies. Hence, accuracy will also increase. We will discuss the proposed model with appropriate diagrams in detail.

A. Convolution Neural Network

We propose a 3D convolution neural network here as medical scans will be used by the model to predict cancerous cells in the CT images. The main purpose of using a CNN is that the three parameters - height, length and depth of the image shall be studied [14]. In addition, the CNN scans smaller portions of the image which makes it easier over the other networks. This network efficiently organises the images and identifies the object in its motion. Moreover, most medical images will have higher resolutions that will require a convolution network to train, test and predict the objective of the model. In [13], 3D network is preferred over 2D due to the constraints in the resolution. Therefore, this model will also use a 3D network for prediction considering CT images with high resolutions divided into training datasets and test datasets.

Further, in [6] the pooling layer is a very essential element in the CNN for training purposes. There are two types of pooling namely max pooling and average pooling. However, both the pooling techniques can not be used in the same model. We propose a max-down pooling layer that will take the maximum value of the stipulated area moving downwards. The pooling layer helps in identifying the hidden features from the network [7]. The pooling layer in the proposed model will crop the image with maximum anomalies within the given area thereby achieving localisation. The max-down pooling attribute will used to crop the area with the maximum number of spots on the CT image. The layer with the maximum value will be studied in the decreasing order. Thus pooling will help us achieve sorting of the patches.
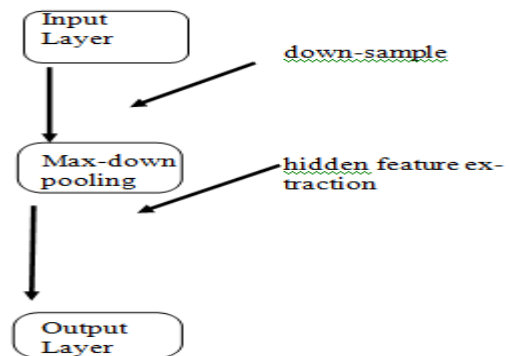

Fig 3: The proposed network with the down-sample concept introduced before max-down pooling extracting hidden features from the pooling layer

Table: The expected resolution of the image after max-down pooling of the CT images.

Length	Breath	Height
252	252	252
128	128	128

B. Datasets

The datasets will be acquired from medical institutions or databases that is available online. The training datasets and test datasets will be organised in such a way that no two images will be identical. Initially the model will be trained with higher resolution images followed by the blurred images so that even the lower resolution images can be used for prediction. Therefore, the accuracy of the model will increase and it can also be reliable compared to the other prediction models. Thus, sufficient focus will be given for datasets.

C. Training

The model will have to be trained from start due to the lack of an existing 3D CNN network. Initially, the network will be built using the training dataset consisting of possible 3D CT images collected from databases. However, the network will only be able to detect clear images.

Therefore, blurred images will also be fed into the network for training purposes. This way the model will be able to predict images. Further, the network will be tested using the test dataset to test the efficiency of the model. As the training progresses, a validation factor will be introduced for accuracy purposes by increasing the hidden layers.

IV.   RESULT

The proposed system is designed for magnification purpose where an area of the image is magnified to identify cancerous cells in the CT scan. The expected outcome of the model will be 'cancer' or 'not cancer'. When the input image is fed into the network, the predicted results will be displayed as mentioned.

$$prediction = \text{'cancer'}$$

Thus, the proposed model will be able to predict cancerous cells efficiently.

The expectant graph of local magnification against the accuracy of prediction will be as follows,
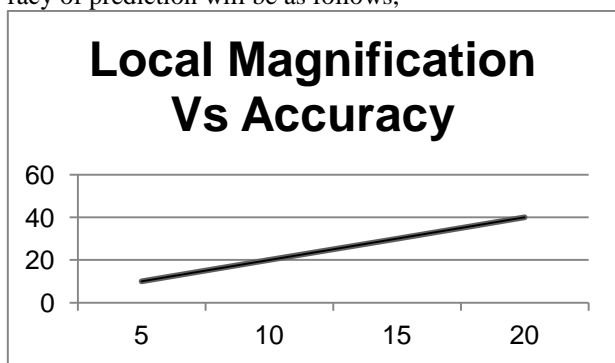
V.   CONCLUSION AND FUTURE WORK

Research so far has made cancer diagnosis easier and more efficient. Early stage lung cancer detection has alarmingly decreased the death rate across the globe. Artificial intelligence has contributed extensively towards the prediction and diagnosis of cancer lately, of which Deep Learning has gained importance. This paper has considered the local magnification factor that has very recently acquired importance in the detection of lung cancer. The existence of very minimal research in this field acted as the driving force towards this research.

The paper proposes an efficient network giving importance to local magnification of 3D CNN in order to predict lung cancer at a much early stage. The model proposes a down-sample concept that scans the images from the top to bottom considering local magnification as an important feature. The max-down pooling layer is expected to extract hidden features from the neurons present. The datasets collected according to the objective of the model is an additional factor that is considered for the construction of the model. The resolution of the images also play a vital role in the training of the model. However, the model only aims at classifying the CT images for prediction purposes. Further research on building a network that utilises a variety of images will increase the efficiency of the model. More focus should be given to the sample sizes of the images to help predict cancerous cells more efficiently. The sample size will help in isolating the cancerous portion of the image from the rest of the CT scan. Improved localisation techniques can enhance the prediction process of the model. Thus, this paper formulates ideas for early lung cancer detection in the view of reducing mortality rates.

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