Lung Cancer Detection Using Deep Neural Networks

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Abstract— As a result of uncontrollable lung cell development, lung cancer typically affects both men and women. This represents a serious respiratory issue that affects both chest inhalation and exhalation. According to a global health organisation, tobacco smoke and cigarette smoking are the leading causes of lung cancer. In comparison to other cancers, the death rate from lung cancer is increasing daily among both young and old people. The mortality rate is not yet being thoroughly monitored, despite the availability of high-tech medical facilities for effective and efficient medical care. This project proposes a system that can be used for the automatic identification of the Lung cancer from the Lung CT-Scan images. In this method, the features of the Lung CT-Scan images are extracted by using the deep convolutional neural networks (CNN) based VGG-16 model, and then the features extracted from the images are then used to train machine learning models that can accurately classify Lung CT-Scan images into Cancer or Non-Cancer. This system enables us to detect the Lung cancer patients in a better and more accurate way.

Indexed Terms— CT-SCAN, CNN, VGG-16

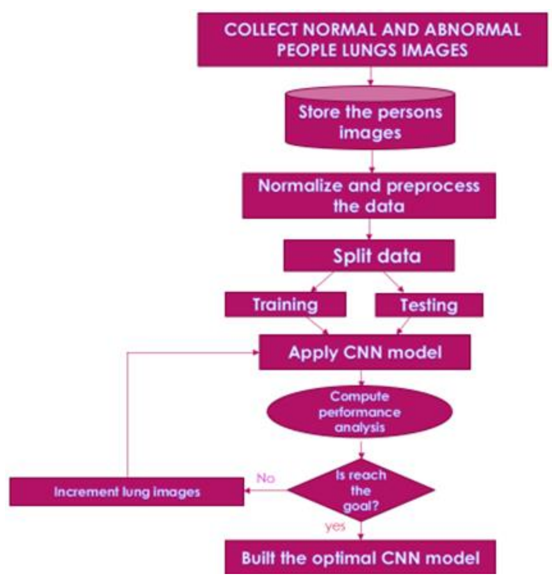
I. INTRODUCTION

In the world, lung cancer is regarded as the second most common type of cancer in both sexes. Lung cancer causes 1.3 million lives globally each year, according to the World Health Organization (WHO). Each year, it is anticipated that there are over 228,820 new instances of lung cancer (116,300 men and 112,520 women), and there are roughly 135,720 fatalities due to this illness (72,500 men and 63,220 women). The abnormal cell proliferation in the lung tissue that characterises lung cancer is known as a malignant tumour.

This is crucial for enhancing the clinical condition of patients. Thus, it is necessary to present an intelligent algorithm for the early diagnosing of lung cancer. Pulmonary nodules are round or oval lung tissue lumps with a diameter of less than 30 mm that can be seen on CT scans. They exhibit significant differences in size, density, position, and surrounding. According to, lung nodules typically have a diameter greater than 3 mm.

Additionally, the rapid advancement of CT screening for lung cancer has resulted in an exponential rise in the amount of image data that must be examined by physicians, significantly increasing their workload and increasing the likelihood that patients will receive an incorrect diagnosis that will increase their risk of being cured. Therefore, with the aim of reducing the radiologist's workload and improving the early detection of lung cancer, numerous methods and systems have been proposed for automatic medical images analysis.

II. PROPOSED MODEL



III. LITERATURE SURVEY

In recent years, researchers have investigated and analyzed Lung CT scan images using deep learning algorithms to detect lung cancer is present or not.. First, the images are preprocessed using the CNN technique for extracting better features, which are fed in deep learning algorithms for image classification.

CNNs have been used frequently in the field of medical image processing image classification and so on [2]. CNNs have already shown inspiring outcomes in the domain of microscopic images classification, such as: human epithelial 2 cell image classification [3], diabetic retinopathy fundus image classification [4], cervical cell classification [5] and Lung cancer detection [6-9]. Brinker et al. [10] presented the first systematic study on classifying the Lung cancer diseases. The authors specifically focus on the application of CNN for the classification of Lung cancer.

Authors in [12] presented the first comparison of CNN with the international group of 58 dermatologist for the classification of the Lung cancer. Most dermatologists were outperformed by the CNN. Authors concluded that, irrespective of any physicians' experience, they may benefit from assistance by a CNN's image classification. Google's Inception v4 CNN architecture was trained and validated using dermoscopic images and corresponding diagnoses. Marchetti et al. [13] performed cross-sectional study using 100 randomly selected dermoscopic images (50 melanomas, 44 nevi, and 6 lentigines).

IV. METHODOLOGY

CNN:
It has 3 layers:
1. The convolutional layer
2. The Pooling layers
3. The output layers

1.The Convolution Layer:
In a convolutional neural network, the linear process is represented by a convolutional layer. To recover various features, each node in the buried layer employs feature detectors for image processing. The first node in the first layer, for instance, may extract the horizontal edges of an image, whereas the second node can extract the vertical edges, and so on. These traits are retrieved with the help of a kernel. Convolution's main objective in the context of a ConvNet is to extract features from the input image. Convolution preserves the spatial link between pixels by observing visual features with tiny squares of input data.

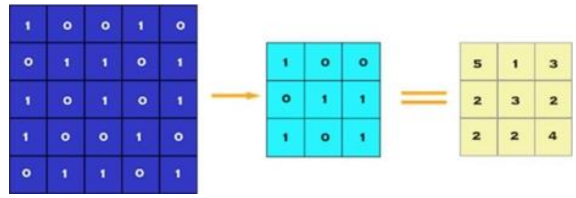


FIG.1 Activation map

2.The Pooling Layer:
Spatial pooling decreases the dimensionality of each function map while keeping the most relevant data. There are some methods of spatial pooling: Max, Average, Total, and so on. We take stride bystride and take the highest value in each area as we slide our window. Our function map's dimensionality is reduced as a result of this. Pooling has the goal of gradually shrinking the input representation's spatial size. It helps in reducing the size and complexity of the input representation. It controls overfitting by reducing the network's number of parameters and computations. It renders the network insensitive to minor transformations, distortions, and translations in the input image.

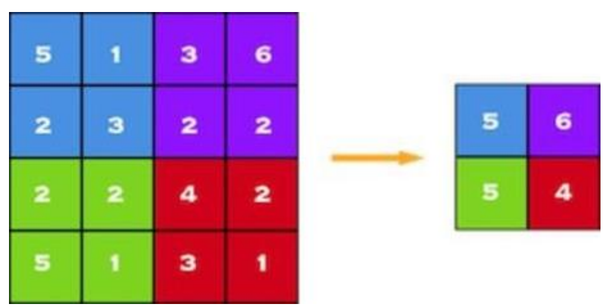


FIG.2 Maxpooling 2x2

3.Fully Connected Layer:
Standard Multi-Layer Perceptrons with SoftMax activation make up the Fully Connected layer in the output layer. Similar to a hidden layer in a neural network, it operates by flattening the number of outputs from each layer, using each value as an input for the following layer, followed by an activation function and an output.

The high-level properties of the input image are reflected in the output of the top two layers. The Fully Connected layer's objective is to classify the input image into several groups using the training dataset as a guide utilising these features and the Fully Connected layer.

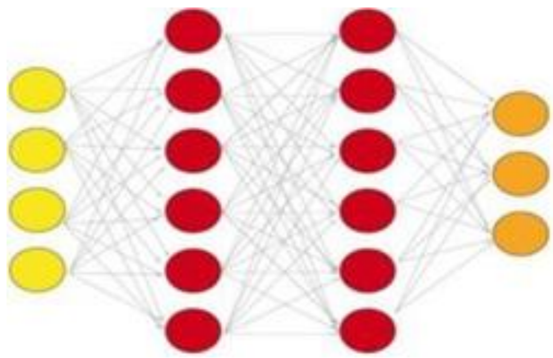


FIG.3 Fully connected layer with two hidden layers

VGG-16:

VGG-16 is a convolutional neural network architecture named after the VISUALGEOMETRY GROUP from Oxford who developed it. There are 16 layers with learnable weights.

Architecture:

The input to cov1 layer is of fixed size 224 x 224 RGB image. The image is passed through a stack of convolutional (conv.) layers, where the filters were used with a very small receptive field:3×3 (which is the smallest size to capture the notion of left/right, up/down, center). In one of the configurations, it also utilizes 1×1 convolution filters, which can be seen as a linear transformation of the input channels (followed by non-linearity). The convolution stride is fixed to 1 pixel; the spatialpadding of conv. layer input is such that the spatial resolution is preserved after convolution, i.e., thepadding is 1-pixel for 3×3 conv. layers. Spatial pooling is carried out by five max-pooling layers, which follow some of the conv. layers (not all the conv. layers are followed by max-pooling). Max- pooling is performed over a 2×2pixel window, with stride 2.

Following a stack of convolutional layers (which varies in depth across different designs), three Fully-Connected (FC) layers are used: the first two have 4096 channels apiece, while the third performs 1000-way ILSVRC classification and so has 1000 channels (one for each class). The soft-max layer is the last one. In all networks, the fully connected layers have the same configuration.

Rectification (ReLu) non-linearity is a feature that all hidden layers have. It should be noted that none of the networks (except from one) incorporate Local Response Normalization, which increases memory usage and computation time without improving performance on the ILSVRC dataset.

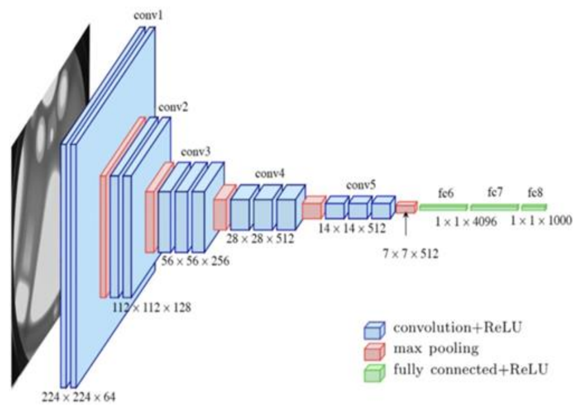


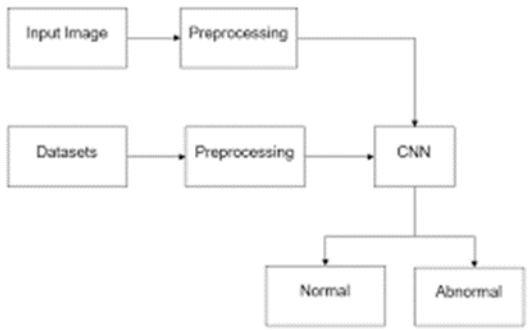
FIG.4 Architecture of VGG-16

- For layer1 and layer 2 the dimensions are 224*224*64, after applying max pooling layer from one of the CNN layers with size 2*2 ,the output dimension i.e.. The size of the lung image is reduced to 112*112*64
- Here 112*112 is the size of the image which is reduced from 224 to 112.
- 64 is the channel i.e…width of the image which is increased.

No	Convolution	Output Dimension	Pooling	Output Dimension
layer 1&2	convolution layer of 64 channel of 3x3 kernel with padding 1, stride 1	224x224x64	Max pool stride=2, size 2x2	112x112x64
layer3&4	convolution layer of 128 channel of 3x3 kernel	112x112x128	Max pool stride=2, size 2x2	56x56x128
layer5,6,7	convolution layer of 256 channel of 3x3 kernel	56x56x256	Max pool stride=2, size 2x2	28x28x256
layer8,9,10	Convolution layer of 512 channel of 3x3 kernel	28x28x512	Max pool stride=2, size 2x2	14x14x512
layer11,12,13	Convolution layer of 512 channel of 3x3 kernel	14x14x512	Max pool stride=2, size 2x2	7x7x512

FIG.5 Tabular form of VGG-16

BLOCK DIAGRAM:



DATA PRE-PROCESSING:

To prepare picture data for model input, preprocessing is necessary. Convolutional neural networks, for instance, demanded uniformly sized arrays of pictures for their fully connected layers. Additionally, model preprocessing may shorten model training time and quicken model inference. Reducing the size of input images will greatly speed up model training time without significantly affecting model performance if the input images are extremely huge. For instance, the typical image size for the iPhone 11 is 3024 4032. Before the output is rescaled back to full size, the machine learning model Apple employs to construct masks and apply Portrait Mode performs on images half this size.

Image data augmentation is a technique for artificially increasing the size of a training dataset by creating modified copies of the dataset's images. We use operations like shear range, zoom range, horizontal and vertical flips, etc. in data augmentation so that we can change the original image by flipping, zooming, or changing the angle in order to create new datasets.

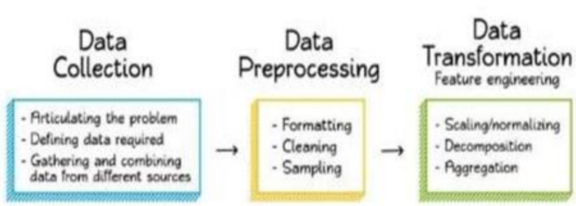
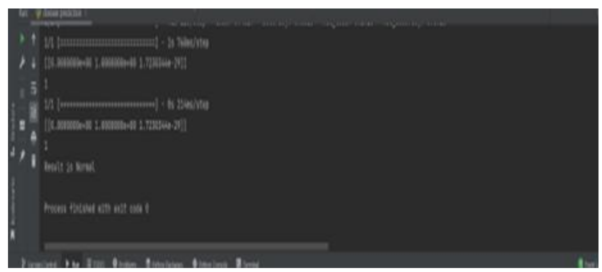


FIG.6 Data Pre-Processing

RESULTS:

To detect cancer tissues in the input lung CT image, a convolutional neural network-based system was used i.e VGG-16 model. The machine has been trained using a lung picture of various shapes and sizes of cancerous tissues. The proposed system is able to detect the presence and absence of cancerous cells with accuracy of about 93% and loss accuracy with 19% after running it for about 02 epoch.

In this we can see that, The "Person is affected by Lung Cancer", with accuracy of 93%



In this we can see that, The person is not affected with lung cancer i.e., "Result is Normal"

CONCLUSION

Early-stage malignancies have been identified using picture recognition technology so that the patient can receive treatment. In order to identify suspicious tissue in target x-ray pictures, the Time is crucial. The study's image efficiency and clarity are two of its most crucial components. The experimental Results show the suggested VGG16 system's advantage in lung cancer detection Pixel. The important elements for determining correct picture comparison are percentage and mask labelling, which show that In order to prevent the disease from progressing to its most severe stages and to lower its mechanism that distributes a globally Medical science should make advantage of learning algorithms. since they improve methodology.

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