Detection of Lung Cancer using concepts of Convolutional Neural Network in Machine Learning

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ABSTRACT

Lung cancer is a life-threatening disease that is time consuming to detect. The survival rate of patients who are suffering from this disease is very low. We need a model that detects lung cancer effectively so that proper measures can be taken to improve the survival rate of the people affected by it. Hence, a new model using a classifier based on CNNs to detect lung cancer in CT images of various patients is proposed in this paper. In this model, we pursue an approach in which we initially build the Convolutional Neural Network. This process is followed by the fitting of Convolutional Neural Network into images, which results in a trained system. This trained system is then tested with some more images and is then capable of determining the presence of lung cancer in images on its own, and classify the images as containing cancer or not, effectively.

Keywords:

Lung Cancer, Convolutional Neural Network, Trained system, CT Scan images, Deep learning, Machine learning

1. INTRODUCTION

Lung cancer is caused due to cell growth in the lungs which ends up spreading to the rest of the body. These form tumors, namely, benign and malignant, in which benign tumors consist of cells which are not cancerous and malignant tumors are the opposite. Among the different types of lung cancer, namely SCLC, NSCLC and lung carcinoid tumor, NSCLC is the most prominent [1]. In its initial stages, the cancer cells stay within the lungs but as time passes, it spreads all over the chest and then moves to the rest of the body [2]. Due to this, only a few patients suffering from this disease survive [3]. Hence, it is very important to detect the cancer as soon as possible, to prevent further spreading and improve the survival rate of the people suffering from it.

We found that the concepts of deep learning, especially the CNNs are very effective in the detection of lung cancer. CNNs consist of multiple deeply connected collection of layers of artificial neural networks [4]. They are very useful and perform very well on tasks like classifying images, detection of objects and various other recognition tasks [5].

The problem at hand is the detection of lung cancer in images of lung CT scans obtained from different patients by classifying those images as healthy or containing lung cancer. This is done by providing as input various CT scan images of lungs containing cancer as well as healthy lungs to the classifier built using CNNs and the result is the correct binary classification. This will lead to effective detection of lung cancer in patients at cheaper rates thereby increasing survival rates of patients. Such a model is described in this paper.

In Section II, we mention some of the works done in order to detect lung cancer effectively. In Section III, we propose the new model and describe the methodology used in this model to detect lung cancer using a classifier based on CNN. Section IV describes the results acquired by training and testing the model using a small dataset. This paper is concluded in Section V by mentioning the future works to be carried out to improve this model.

2. RELATED WORK

There are several works carried out to simplify the detection of lung cancer.

In [6], classification of lung cancer into the two types, namely, benign and malignant by using CNNs is demonstrated. The dataset is taken from LIDC and CT scans from 71 patients is used. This dataset is processed and converted to HDF5 format. According to the proposed CanNet architecture, the dataset is fed to the first convolution layer, the output from which is given to the ReLU layer, followed by the second convolution layer and another ReLU layer and the result from this is made to pass through a layer which performs max-pooling. The result is then input to a dropout layer. The final classification is done in the fully connected layer. The results show that CanNet performs better that ANN and LeNet.

In [7], description of a method which uses 3D CNNs to detect pulmonary nodules by itself is given. A dataset consisting of 1500 CT scans are used for this process. Initially these are converted from grayscale to RGB, after which it is processed and a final mask containing the region of interest is obtained. 3D CNNs which makes use of the ReLU activation function, a softmax layer and a fully-connected layer is used. SVM classification results when performed on the same dataset is also analysed and it is found that 3D CNNs perform better and give more accuracy.

In [8], the first step for cancer nodule detection is image pre-processing. It is used to remove the unnecessary features from the CT images. The pre-processing steps include image smoothening, image enhancement and image segmentation. For this step image smoothing median filter was used, Gabor filter is used image enhancement, and useful features are extracted by applying image segmentation to the image. The next step is feature extraction where features like eccentricity, area and perimeter is identified. The last step is the classification step where SVM algorithm was used for the given purpose and they have used non-linear classifier. The stage of the lung cancer can be determined by the area of the tumour in lung.

In [9], experiments have been conducted with different types of training functions used in neural networks to check which yields the best classification results. Some of the training functions they have used are Resilient back propagation, Automated Regularization, One Step Secant Algorithm and other 10 functions. In this paper, they have proposed two training functions. Training function 1 includes the learning rate and momentum factor and training function 2 is modified such that it reduces the mean square error.

In [10], A neural network-based algorithm namely Entropy degradation method (EDM) has been proposed. In this technique the input provided is that of CT Scan images. This is used for the detection of small Lung Cancer. EDM provides a reasonably good prediction accuracy. Providing an accuracy of 77.8% where the input provided to the training and testing dataset is CT scanning Images.

In this paper [11], the different technologies that are existing and are present up to date have been provided. While presented with the input we should first know whether the dataset provided is of patients is smokers, or non-smokers, that is, healthy lungs. Also, if they have any prior history of malignancy. They showed the various progress made, detection, validation and prediction using different models and the nodule classifications is done using different software.

In [12], a screening method of thoracic Computed Tomography is used, and the problems associated with the classification of lung nodules have been found. Since nodules are heterogeneous in nature, a learning framework called Multi-Scale Convolutional Neural Networks (MCNN) is used to extract the different features. This framework uses a hierarchical approach. It successfully classifies the benign and malignant nodules.

3. METHODOLOGY

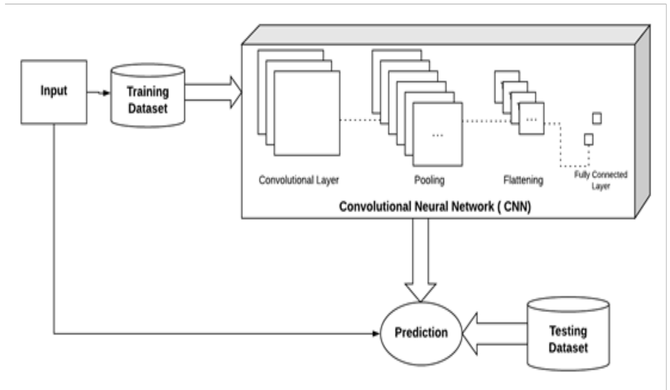

Figure 1. System Architecture

In this section, the working of Convolutional Neural Network is explained. There are three main steps in the process; Building the convolutional neural networks, fitting the neural networks to the images and finally making new predictions based on the observations. The concepts of neural networks along with deep learning are used in the entire project. The various processes involved in building the system for the detection of lung cancer are shown in Fig 1.

The system mainly uses the Keras library to create deep neural networks with few lines of code. Keras wraps the properties of Theano and TensorFlow libraries and runs on these platforms. It is highly efficient for fast numerical computations based on NumPy syntax. It runs on both CPU as well as GPU and is more powerful since it can handle floating point calculations. It mainly emphasises on parallel computations. A convolutional neural network model is built by initialising a sequential class that contains a linear stack of layers. Convolution is then applied on the input image to reduce its size and to detect some important features of the image. The features are then pooled to reduce the number of parameters and to reduce overfitting. These pooled features are then converted to a column-wise pattern that is input to the neural network. A whole artificial neural network is then added to the convolutional network to optimize the output.

a. Building the Convolutional Neural Network

The algorithm runs on TensorFlow platform and is based on the transfer learning methodology. The classifier has been pre trained to perform basic classification based on supervised learning methodology. This algorithm is retained for the border threat dataset to classify various levels of threats. Based on how big the dataset is and how well it is trained, the algorithm classifies new images. In this stage, we first initialize the convolutional neural network by defining a sequential constructor. This sequential constructor contains a linear stack of layers.

3.1.1 Convolution

Convolutional layers can give the best optimisation of its output and can also lower the complexity of the model. Optimization is done using depth, stride and zero-padding which are called hyper parameters. The depth is set manually by considering the neurons within the layer. This depth is usually of the output volume produced by the convolutional layers. Stride is to set the depth to place the receptive field around the spatial dimensionality of the input. Zero-padding is a method of padding the input border. It can be also used to control the dimensionality of the output volumes [6].

$$Zero\ padding = \frac{(n-1)}{2} \tag{1}$$

n here used in the equation is the filter being used.

Different filters are applied to the input image and corresponding feature maps are obtained. The feature maps help in reducing the size of the images are hence faster to process. Though some information is lost while creating these maps, these help in extracting the integral parts of the images. The highest number in the feature maps correspond to the best pattern match. Since it is the features that we recognize and not every pixel in the image, these feature maps are found to be very useful. It helps us get rid of all the unnecessary details and highlights the best features. To preserve information, multiple feature maps are created by applying different filters. The system then learns from its training and decides which features have to be preserved.

A rectified linear unit (ReLU) is then applied to these convolutional layers that increases the non-linearity of our images. Since images are non-linear in nature because of different elements in it, it may so happen that applying convolution on them will reduce linearity. Hence a rectifier is necessary to overcome this issue.

3.1.2 Max Pooling

Pooling is mainly done to down-sample and reduce the complexity for further layers. It can be considered similar to reduction in the resolution of the image in the image processing domain. The image obtained in this step is partitioned into rectangles, and the maximum value of a sub-region is returned. Usually, a 2×2 matrix is considered for max pooling [4]. The neural network should have the capability to identify the features in case of distortion. For this, the feature map is converted into pooled feature map. The pooled feature maps contain a combination of features from its immediate neighbours. It not only reduces the size, but also preserves the integrity of the features. The maximum value is pooled in this method and hence this accounts for spatial distortion. It disregards 75% of non-important information and prevents overfitting.

3.1.3 Flattening

The pooled feature map is then converted into one huge column-wise vector that is input to the ANN for further processing.

3.1.4 Full Connection

In this stage, a whole artificial neural network is added to the convolution network. A fully-connected layer is used which connects every node in the previous layer as well as next layer [4]. There is a connection between neurons of the fully-connected layer with the neurons in the adjacent layers but has no connection with the layers between them. The purpose of this is to deal with the existing attributes, come up with new attributes and then combine these to predict things in a better way. The values from the convolutional layer are first passed onto the artificial neural networks. Predictions are made based on the information obtained from the layers. In case there are errors in the predictions, these errors are calculated and backpropagated. The weights are adjusted to optimize the network. In addition to weights, feature detectors are also adjusted to make sure that we are looking at the right features. This is repeated several times and this is how the network gets trained. The data propagates throughout the network and the errors are compared. There are two output neurons in this case. One detects the presence of lung cancer, while the other detects the absence of lung cancer. The highest values from the layers are sent to both the outputs. Depending on the images and the features extracted, the trained system has to identify whether the image contains cancerous cells or not. The decision is taken after quite a large number of iterations. The output size of the given convolutional layer is given by

$$L = \frac{i-f+2t}{d} + 1 \tag{2}$$

Here, L is the output and i is the input both of which corresponds to the height and length, the padding, stride value and also the filter is given by t, d and f respectively.

b. Fitting the convolutional neural network into images

In this method, the images are first augmented. Image augmentation is a technique that enriches our training set without adding more images and gets us good performance results with a small fraction of images. This helps in reducing overfitting. Image augmentation is first applied on the images which involve several transformations like rescaling, shearing, zooming, etc. A training set is then created that contains the augmented images extracted from the image data generator. The test set is then used for evaluation from model fit. This technique fits the convolutional neural networks on training set and then tests its performance on the test set.

c. Making new predictions

In the final stage we expect our CNN model to predict the images provided by the user. We need to pre-process the image that we can later load so that it can be accepted by the predict method that we are going use to make the prediction. This can be done by using a load function. Once the image is loaded, we can find out the type and dimension of the image. The functions of the neural network like the predict function cannot accept a single input by itself as it accepts inputs in a batch. We can have several batches of several inputs to which the predict method can be applied. Once we get the output, we need to find out the resulting prediction corresponds to which of the input images. By using attributes, we can show the mapping between the images. We can also use conditions to check whether our prediction is correct or wrong.

4. RESULTS

The lung cancer CT scans used for this process is obtained from an archive called The Cancer Imaging Archive (TCIA). The dataset contains lung CT scans of 32 patients suffering from cancer. The images are in DICOM format which we convert to JPEG format. This dataset is divided into two sets, namely, training set and test set, each having two classes i.e., lung cancer and not lung cancer. The training set consists of 175 images in each class. The test set consists of 75 images in each class. This dataset is used to train the system and perform validation on it. A single image can then be used for detection.

The results obtained for the two types of classifications, namely, lung cancer and not lung cancer, are shown below.

Figure 2. CT image with Cancer

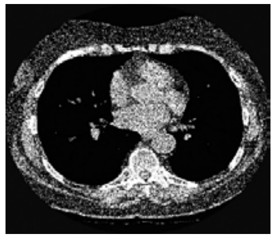

Figure 3. CT image without Cancer

Fig 2 is the CT image used for single prediction in the case of lung cancer and Fig 3 is the CT image used for single prediction in the case of healthy lungs.

The corresponding prediction results obtained are given in the following figures.

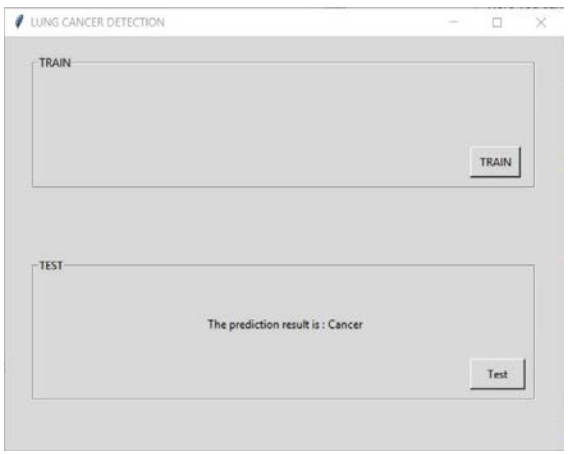

Figure 4. Prediction result with Figure 2 as the image to be predicted.

Fig 4 indicates that the result of the prediction process is lung cancer when Fig 2 is used as the image to be detected.

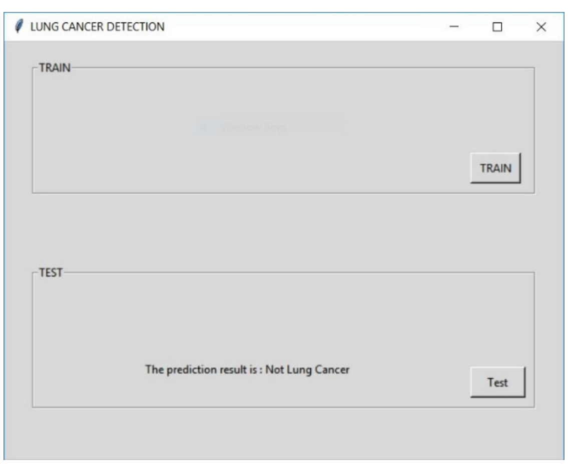

Figure 5. Prediction result with Figure 3 as the image to be predicted.

Fig 5 indicates that the result of the prediction process is not lung cancer when Fig 3 is used as the image to be detected.
Accuracy can be calculated using the formula

$$Accuracy = \frac{TC+TNC}{TC+TNC+FC+FNC} \tag{3}$$

Where TC represents true cancerous, TNC represents true non-cancerous FC represents false cancerous and FNC represents false non-cancerous.
The following plots further describes the results.

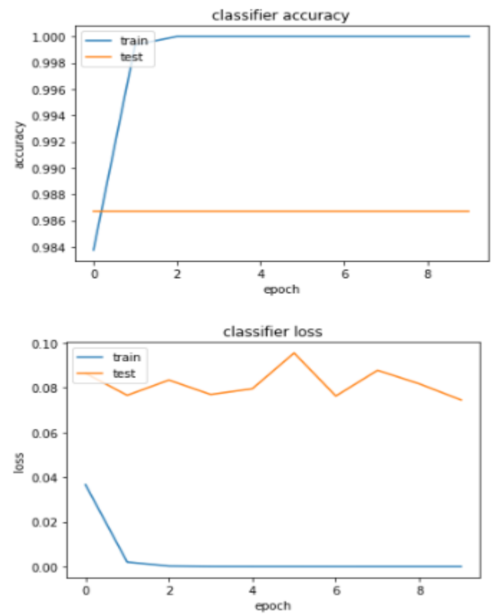

Figure 6. Accuracy vs. Epoch for CNN classifier

In Fig 6, the plots describing the accuracy obtained and loss endured by the classifier with Fig 2 as the image used for detection over 10 epochs is shown.

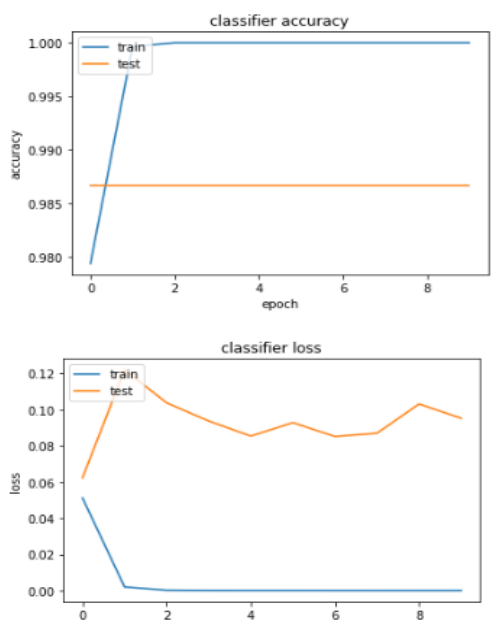

Figure 7. Accuracy vs. Epoch for CNN classifier

In Fig 7, the plots describing the accuracy obtained and loss endured by the classifier with Fig 3 as the image used for detection over 10 epochs is shown.

In Fig 6 and Fig 7, the blue plot indicates training and the orange plot indicates testing. In both these figures, we can see that the classifier training accuracy increases with the increase in the epochs and reaches maximum, while the testing accuracy is steady, indicating that the dataset is not sufficient because it has already reached its maximum with the small dataset used. We can also see that the loss in the case of training decreases to the minimum while the loss incurred during testing is variable, but higher. This is due to the small dataset used, which accounts for the smaller number of features learnt by the system. As the number of features learnt are less, the unfamiliar images given to the system returns variable losses. This can be improved by providing a larger dataset for both training and testing, thereby reducing losses and improving the performance of the CNN classifier.

The results indicate that this CNN based classifier detects lung cancer in CT scans effectively. The increase in the losses and accuracy is due to the small dataset used and can be improved when a larger dataset is used.

5. CONCLUSION

Nowadays, a large number of people are being affected by lung cancer which is a dangerous disease. We want to propose a new model other than the existing ones in order to detect lung cancer in individuals. Previously, detection of lung cancer was done using various existing techniques, but they all have some limitations. Deep learning methods, especially convolutional networks include multi-layer processing. The advantage of this method is it takes lesser time and provides better accuracy in performance. Convolutional networks require a lot of data and strong processing power. In our proposed model, we pursue an approach in which we initially build the neural network that is the Convolutional Neural Network and then fit the CNN into images. The result obtained is then passed to the various layers of the network where it undergoes many iterations which will train the system. The trained system is now capable of making better predictions i.e., whether the given image is cancerous or not. In future, this technique can be used to detect different stages of cancer.

REFERENCES

[1] Kalaivani, S., Chatterjee, P., Juyal, S., & Gupta, R. (2017, April). Lung cancer detection using digital image processing and artificial neural networks. In 2017 International conference of Electronics, Communication and Aerospace Technology (ICECA) (Vol. 2, pp. 100-103). IEEE.

[2] Shandilya, S., & Chandankhede, C. (2017, March). Survey on recent cancer classification systems for cancer diagnosis. In 2017 International Conference on Wireless Communications, Signal Processing and Networking (WiSPNET) (pp. 2590-2594). IEEE.

[3] Kulkarni, A., & Panditrao, A. (2014, May). Classification of lung cancer stages on CT scan images using image processing. In 2014 IEEE International Conference on Advanced Communications, Control and Computing Technologies (pp. 1384-1388). IEEE.

[4] Albawi, S., Mohammed, T. A., & Al-Zawi, S. (2017, August). Understanding of a convolutional neural network. In 2017 International Conference on Engineering and Technology (ICET) (pp. 1-6). IEEE.

[5] Guo, T., Dong, J., Li, H., & Gao, Y. (2017, March). Simple convolutional neural network on image classification. In 2017 IEEE 2nd International Conference on Big Data Analysis (ICBDA) (pp. 721-724). IEEE.

[6] Rao, P., Pereira, N. A., & Srinivasan, R. (2016, December). Convolutional neural networks for lung cancer screening in computed tomography (CT) scans. In 2016 2nd International Conference on Contemporary Computing and Informatics (IC3I) (pp. 489-493). IEEE.

[7] Fan, L., Xia, Z., Zhang, X., & Feng, X. (2017, October). Lung nodule detection based on 3D convolutional neural networks. In 2017 International Conference on the Frontiers and Advances in Data Science (FADS) (pp. 7-10). IEEE.

[8] Tang, H., Kim, D. R., & Xie, X. (2018, April). Automated pulmonary nodule detection using 3D deep convolutional neural networks. In 2018 IEEE 15th International Symposium on Biomedical Imaging (ISBI 2018) (pp. 523-526). IEEE.

[9] Kuruvilla, J., & Gunavathi, K. (2014). Lung cancer classification using neural networks for CT images. Computer methods and programs in biomedicine, 113(1), 202-209.

[10] Q. Wu and W. Zhao, "Small-Cell Lung Cancer Detection Using a Supervised Machine Learning Algorithm," 2017 International Symposium on Computer Science and Intelligent Controls (ISCSIC), Budapest, 2017, pp. 88-91.

[11] Gleeson F and Kadir T, Lung cancer prediction using machine learning and advanced imaging techniques. Transac Lung Cancer Res 2018; 7(3):304-312.

[12] Lo, S. C., Lou, S. L., Lin, J. S., Freedman, M. T., Chien, M. V., & Mun, S. K. (1995). Artificial convolution neural network techniques and applications for lung nodule detection. IEEE Transactions on Medical Imaging, 14(4), 711-718.