Lung cancer medical image recognition using Deep Neural Networks

Dr.M.Rajaiah[1] , Dean Academics & HOD, Dept of CSE, Audisankara College of Engineering and Technology, Gudur.

Mr. A .Hemanth Kumar[2] **,** Associate Professor**,** Dept of CSE, Audisankara College of Engineering and Technology, Gudur.

B. Sai [3]**,** UG Scholar, Dept of CSE, Audisankara College of Engineering and Technology, Gudur.

D. Vishaka[3]**,** UG Scholar, Dept of CSE, Audisankara College of Engineering and Technology, Gudur.

G. Sirisha[4]**,** UG Scholar, Dept of CSE, Audisankara College of Engineering and Technology, Gudur.

K. Balaji[5] ,UG Scholar, Dept of CSE, Audisankara College of Engineering and Technology, Gudur.

Abstract—Medical images (Magnetic Resonance Imaging scans) are used by doctors and medical specialists to determine the possibility that a cancer is present in the lungs of a patient. We are using these images, along with Deep Neural Network algorithms to help doctors with image diagnostics by training the Deep Neural Network (DNN) to recognize lung cancer. Our Deep Neural Network introduces novelty by making extensive search by adding additional layers of convolution and max pooling. Moreover, we are using images from slow progressing lung cancer to determine the threshold or at which point in the progression, our Deep Neural Network, will diagnose the cancer. Using this, doctors will have additional help in early phase lung cancer detection and early treatment. These are the main purposes of our research, which includes thorough search of possibilities of lung cancer and early detection.

Keywords—Deep Neural Networks; Image Recognition; Lung Cancer; Medical Imaging;

I.INTRODUCTION

Latest developments in Deep Learning and Deep Neural Networks facilitate the process of image recognition. Using Deep Neural Networks we can search for patterns in an image and determine if we recognize the pattern or not or we can search for multiple patterns and as a result get which pattern was recognized. Training the Neural Network requires a dataset that is predetermined which the Network can use to learn to recognize.

Deep neural networks are becoming more and more popular as they can be applied to image pattern recognition and image classification. Few other derivative methods emerged, such as, template matching, Support Vector Machine, Deep Restricted Boltzmann, Stacked Autoencoders and Deep Convolutional Networks, [1]. In [2], they are using modified AlexNet model, where instead of using back propagation, they are using unsupervised sparse autoencoder machine. By using this autoencoder, they are accelerating the learning feature success of the Deep Neural Networks to 90.1%. They are testing this feature on Synthetic

Aperture Radar (SAR) images, where the algorithm classifies these images into predetermined classes.

Properly trained Deep Neural Network usually requires large data set and adjustment of many parameters to get border line results, assuming that the algorithm does not overfit. Since, large amounts of medical images is hard to be obtained, other methods are to be used to train the DNN. In [3], they are using active learning to help with the data set, that is to help with selecting and classifying the images before training. They use multistage training scheme to overcome the overfitting problem, which in term means that they start off with a smaller data set, and reduce it up to the point where there is no overfitting. For each next step they predict the amount of data they need to send the DNN and measure if and when overfitting happens.

Image classification is important to reduce the stress of computation put on DNN, but after the algorithm classifies the image, in this case cancerous or not, it may be useful to pinpoint the location where the algorithm detected the malignant tissue. In [4], the authors added a softmax classifier layer for visualization of the result i.e. the affected area of the tissue. The advantage of this approach is that the authors used skin tissue cancer and the images used are RGB images that can be easily classified.

Predictive modeling using Deep Neural Networks is applied in another medical area, in [5], where authors are trying to early diagnose Alzheimer's brain from a regular nonAlzheimer's brain. They are using functional MRI data to train and test the Deep Neural Network model. They are using one convolutional layer to search the images.

We are proposing a lung cancer medical image classifier system that is based on Convolutional Deep Neural Network. To train and test our system, we used Magnetic Resonance Images of lungs which were previously classified by medical specialists and put into piles of YES and NO (yes, the patient is diagnosed with lung cancer and no, the patient is cancer-free). Our system is trained using these images to be able to classify a new unclassified image into a pile and test the network to determine the success rate. When the initial success rate is satisfactory, the system is further tested against an additional dataset. This additional dataset is composed of images outside of the initial lung images and contains medical images of predetermined slow progressing lung cancer. This way we are testing the Neural Network to determine at which point of the cancer progression, the Network will diagnose the cancer. The rest of the paper is structured as follows: the second section presents the architecture of the Deep Neural Network with all its inner
layers. The third section depicts the training and thus
building our system of Deep Neural Network. Section four presents the results of the training and testing of the system, whereas, section five concludes the paper and presents future work.

II. ARCHITECTURE OF THE SYSTEM

Image recognition in Deep Neural Networks is based on image classification, where the Neural Network is trained to classify an image into a list of predetermined piles or types, [4]. In its simplest form, it is used to determine if something was recognized or not. In our case, we are trying to classify medical images and determine if there is cancer or not, so we can simplify the outcome of the recognition as YES or NO (YES there is cancer or NO). The Neural Network has to be trained so that it can be used for image classification. This process takes a list of input data, which is then fed to the network and the outcome of this is compared to the expected outcome. The input data in our case is a large scale CT images that are fed to the network, so the input layer has to have as many input nodes as the size of the array. The output of the network can be a single node 0/1 or it can be an array. In our case it is a binary code that is either 0000 (not cancer) or 0001 (cancer). This is shown on Figure 1. We are using Keras packages in Python combined with TensorFlow libraries to prepare the data, train the network and test it.

A. Data preparation

The data preparation process has to be done precisely, which in our case is done in several stages. The CT images are obtained from a local medical hospital and medical personnel (specialists from the Oncology department) is consulted to classify the images into two piles: possibility of cancer and cancer-free. We have 70 patients, each with 64 slices of CT images, all from different angle. One such angle is shown on Figure 1. In this stage we create two piles, where 58 patients

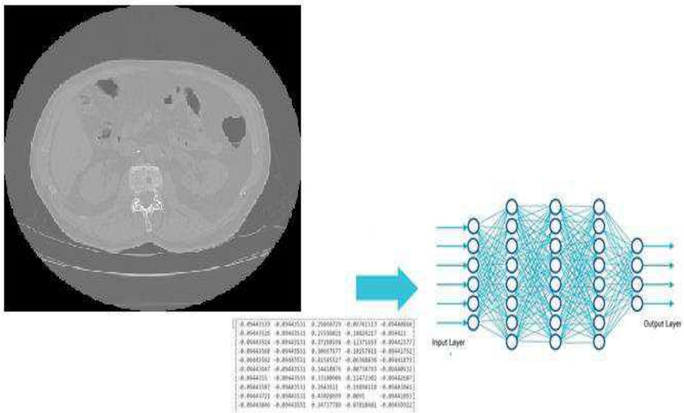


Figure 1 Architecture of the system: converting images and feeding them to the network

After images are ready to be used for training, we are preparing the Neural Network with the additional layers where were diagnosed the possibility of cancer and 12 were cancerfree. Almost all of the images that are with a possibility of a cancer actually were diagnosed with cancer with further analysis.

Next stage is to pile together images of same angle (angle slice), this means that we would get 64 piles of same angle images, each of which will have 58 large scale CT images of possible cancer, and 12 images of cancer free. A sample of different angle CT images is shown in Figure 2. This pilling up is done so that Deep Neural Network will be focused on recognizing same angle images and thus hopefully improve the process.

Additionally, the piles are further divided into training and testing set. In our case, we are using 10% of the images for testing and the other 90% for training. The data is loaded from a batch of images and the images are divided into training and testing set (a subsets [X,Y]). Finally, the data is shuffled and converted to binary class matrix so that they can be fed to the Neural Network.

B. Deep Neural Network

Since the images are ready and in binary matrix form, they can be fed to the Deep Neural Network and train-test it. But the network model has to be formed so that it can be train-tested and this means defining the parameters and layers of the DNN. As mentioned before, the DNN requires larger data set to be train-tested more extensively (precisely), [4], so the images are augmented in order to obtain a larger data set. This means that they are flipped, rotated and skewed, so that more versions of the same image can be used in the training process, and thus the training of the algorithm can use a larger data set created at train time the Deep

ISSN2515-8260 Volume10, Issue 02, 2023

Neural Network appears. The hidden (inner) layers are convolution layer, max pooling, followed by double convolution layers (two convolutions) and an additional max pooling at the end.

The first convolution layer is used so that we can have an initial segmentation of the images. Next, we need to reduce the size with the max pooling layer. The second and the third convolution is done so that we can make a more thorough search of the problem (i.e. the cancer) and obtain more precise knowledge of where the cancer might be. What the convolution does to an image is shown on Figure 3

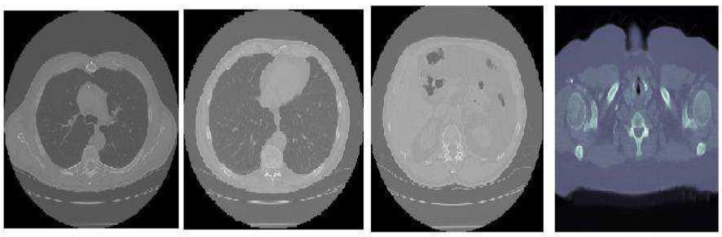


Figure 2 Different angles of CT Lung cancer images

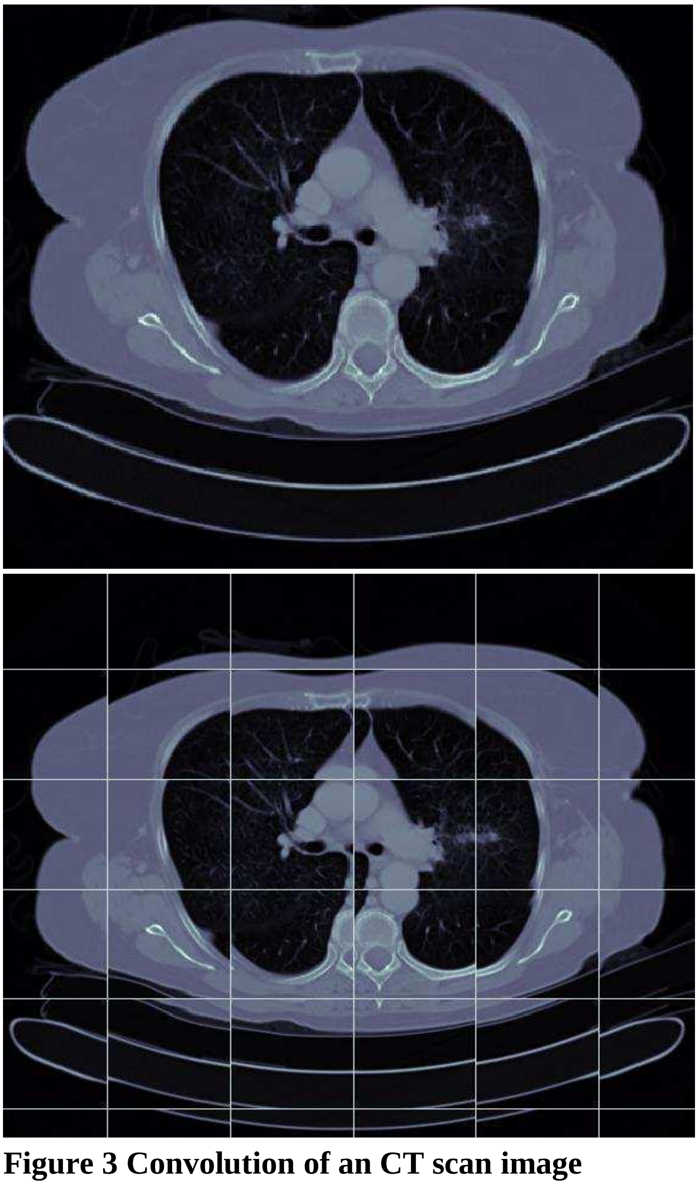


Figure 3 Convolution of an CT scan image

As we can see from Figure 3, we are further slicing the image into parts, where the slices overlap. This way, we can focus (isolate) a certain part of the image and use that image to search for a pattern in the image. This way we can make a thorough search of the cancer in a new image. In our model, we define the convolution parameters and the slicing window. There is a tradeoff here as to how much overlapping there should be. If we increase the overlapping, we are making more window-sliced images and thus more thorough search. But, by doing so, we are slowing down the process and it requires more resources. Since the convolution results in more smaller images from the original one, by using max pooling, we are reducing the size of these images into chunks of data, where we get the most (maximum) of every image. This means that we search for the cancer by upsizing the image in one layer and downsize the results in the next. We can see these layers on Figure 4. At the end, we are defining the learning rate and the dropout factor, that drops out elements that have below 50% of success rate. When the model is defined, the algorithm is then executed using the model and creates the DNN by training and testing it. The training process takes the initial dataset (X,Y) and the testing data set (X_Test, Y_Test). Each epoch (train cycle), the algorithm passes all the images once through the training process. Our training process has 100 epochs to train 64 large scale CT images in one pile. After the training is finished, the network is saved and can be used to classify CT images and determine the possibility of a cancer.

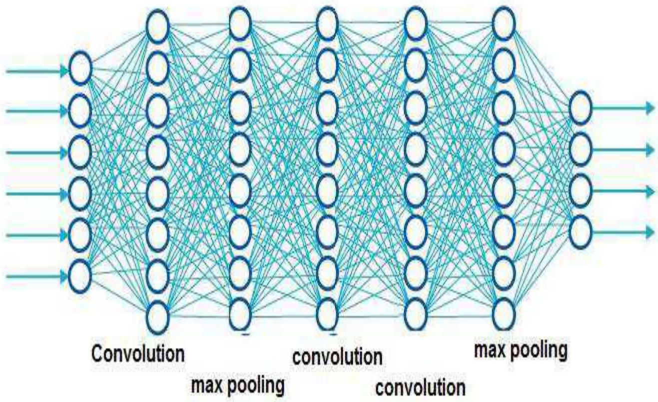
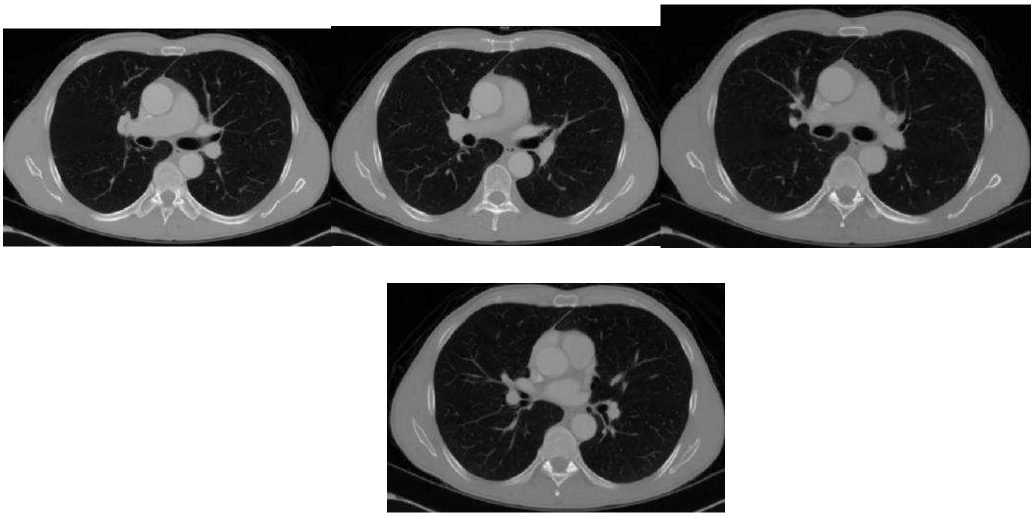


Figure 4 Building the Deep part of the Neural Network with hidden layer

III. RESULTS AND DISCUSSION

One of the main novelties in our Deep Neural Network image recognition architecture is the additional convolution layers coupled with the pre-classification of the CT images before being fed to the network. The other novelty is testing our DNN architecture against a slow progressing lung cancer and determining the threshold at which stage the DNN will detect possibility of a cancer. On Figure 5, we can see the test set of the slow progressing lung cancer CT scans from early to late stage.



In our case, we have 5 stages of slow progressing lung cancer, where each image in Figure 5 represents one of the stages. Stage 0 represents the stage where the tumor is small and hasn't spread to the deeper tissue or outside the lungs. Stage 1 is the stage where the cancer is in the lung but not the lymph, and stage 2 is where the cancer spread to the lymph nodes. Stage 3 is when the cancer has spread to the middle of the chest and stage 4 is the final stage where the cancer has spread throughout the entire body.

For each processed image, our DNN outputs 0000 (cancer free) or 0001 (cancer) and the certainty of detection. We can see from Figure 4 that our DNN detects possibility of cancer with high certainty (above 75%) in the third image. The drawback here is that we have to decide the minimal value of certainty we will accept as being satisfactory. Here we take that 75% certainty is a fair trade. In our case scenario, the DNN always outputs 0001 (possibility of cancer detected) and by using the probability we can decide if there was cancer or not. We can change the DNN to output always 2 values (0000 and 0001) and determine which one has above 75% of certainty. This way we can eliminate around 50% certainty on both possible outputs (0000 and 0001). This way we can classify the image not just as being exclusively 0000 or 0001, but also compare how much is 0000 (not cancer) and how much is 0001 (cancer).

IV. CONCLUSION

Our Deep Neural Network includes layers of convolution that can thoroughly search for anomalies (cancer). Further, the network is using same angle CT images so that it can focus on solving images more accurately. Finally, we are testing our Deep Neural Network with a slow progressing lung cancer, where we can see at which stage, our Deep Neural Network, will detect a possibility of a cancer.

For future work, we are planning on modifying the DNN to show us where on the image it has detected a cancer and using additional python code to mark it on the image.

V. REFERENCES

1) Ivanov, A., Zhilenkov, A., The prospects of use of deep learning neural networks in problems of dynamic images recognition, Russian Young Researchers in Electrical and Electronic Engineering (EIConRus), Russia, 2018
2) Huang, T., Gao, F., Wang, J., Combining Deep Convolutional Neural Network and SVM to SAR Image Target Recognition, International Conference on Internet of Things (iThings) and

IEEE Green Computing and Communications (GreenCom) and IEEE Cyber, Physical and Social Computing (CPSCom) and IEEE Smart Data (SmartData), United Kingdom, 2017

3) Stanitsas, P., Cherian, A., Truskinovsky, A., Active convolutional neural networks for cancerous tissue recognition, International Conference on Image Processing (ICIP), 2017, China
4) Cruz-Roa AA., Arevalo Ovalle JE., Madabhushi A., González Osorio FA., A deep learning architecture for image representation, visual interpretability and automated basal-cell carcinoma cancer detection, Medical Image Computing and Computer-Assisted Intervention – MICCAI 2013, Japan 5. Sarraf, S., Tofinghi, G., Deep learning-based pipeline to recognize Alzheimer's disease using fMRI data, Future Technologies Conference, USA, 2016

AUTHOR PROFILES

Dr.M.Rajaiah , Currently working as an Dean Academics & HOD in the department of CSE at ASCET (Autonomous), Gudur, Tirupathi(DT).He has published more than 35 papers in, Web of Science, Scopus Indexing, UGC Journals.

Mr.A.hemanth kumar, completed his MCA in SV university and he completed his ME at satyabhama university at 2006 he worked as a MCA head in audisankara at 2007 and currently working Accociate professor in the department of CSE at ASCET.

Ms. G.saisireesha , as B.Tech student in the department of CSE at Audisankara College of Engineering and Technology, Gudur.

Mr.B.Sai, as B.Tech student in the department of CSE at Audisankara College of Engineering and Technology, Gudur.

Ms.D.vishkha , as B.Tech student in the department of CSE at Audisankara College of Engineering and Technology, Gudur.

Mr.K.balaji , as B.Tech student in the department of CSE at Audisankara College of Engineering and Technology, Gudur.