Lung Cancer Detection and Classification Using Image Processing and CNN Deep Learning Architecture

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***Abstract*—A large number of cancer deaths in the world is due to lung cancer, which is caused due to unbalanced cell growth. Through our work, a CNN-DEEP learning model is proposed with the help of image pre-processing techniques for detecting and classifying lung cancer in a dataset we aim to help in the diagnosis of the patient's cases: benign, or malignant.**

I. MOTIVATION

Currently, there are many techniques to detect and diagnose lung cancer. Most of the methods used by doctors are a long procedural task and might take some time to diagnose lung cancer. Lung cancer identification at an early stage is both necessary and beneficial to the patient. A low-dose CAT scan or CT scan (LDCT) has been explored on people who are at a greater risk of developing lung cancer in recent years. LDCT scans can aid in the detection of cancerous spots in the lungs. CT scanning also seems to be less harmful than regular chest x-ray scans.

For detecting, an artificial neural network might be employed. of cancer nodules in these CT scan images. A detection model with good accuracy can be used for the early detection of lung cancer as it is the key to increasing survival rates for patients with lung cancer. When cancer is detected early, the chances of effective therapy increase. Certain initial malignancies may have detectable signs and symptoms, however this is not always the case. Following a cancer diagnosis, staging offers critical information about the extent of the disease in the body as well as the expected response to therapy.

II. DATASET AQUISITION

The CT scan images used in this model were taken from the Kaggle dataset. These datasets contain DICOM images.

To read these DICOM images in Matlab, first, we have to use the “dicominfo” function which reads the metadata of the DICOM image and stores it in a variable. The name of the image is given as an argument. Then “dicomread” is used where the dicominfo data is passed as an argument that reads the DICOM image.

The goal of the dataset was to test several techniques for analyzing patterns in CT images that are related to contrast and age of the patient. The fundamental concept is to find visual textures, statistical patterns, and features that are strongly linked to these attributes, then build straightforward tools to automatically recognize these images when they are misclassified(or identifying abnormalities, which could be dubious cases/devices that aren't calibrated properly). It is made up of the middle slices of all CT pictures taken from patients who had valid age, modality, and contrast tags.

III. LITERATURE REVIEW

[1] proposed a framework that used Support Vector Machines (SVM) for classification of cancer as either benign or malignant. In the pre-processing stage, median and gaussian filters are used inorder to remove the noise present in the image. The processed image is segmented using watershed segmentation.

[2]proposed a a framework that used Support Vector Machines (SVM) as its classifier to classify the nodule images into malignant or benign and to classify the lung cells into malignancy levels. Also presented the effectiveness of using Structural Co-Occurrence matrix (SCM) is used for feature extraction.

[3] Implemented an Artificial neural networks as the classifier. Used image pre-processing techniques such as image erosion, median filtering, thresholds and feature extraction. Binarization was used for image segmentation.

[4] suggested the use of a feed forward network that was trained using certain pre-defined attributes. This approach had a training error rate of less than 1% which thereby leads to a better accuracy.

[5] Implemented an algorithm that was composed of two networks: a feature extractor and a classifier. Both models were trained with Adam’s algorithm since the data set was quite large and the images were very noisy.

[6] suggested a new technique of using DTCWT as a feature extractor and PNN as a classifier. The existing

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weights of the PNN will never be alternated but only new vectors are inserted into weight matrices when training.

[7] proposed the use of a fully convolutional neural network (FCN) that used image pre-processing techniques to reduce noise. This network helped in increasing the F1 score.

[8] proposed a network that used histogram equalization and thresholding segmentation in the pre-processing stage. An additional adam algorithm is implemented along with the CNN model.

[9] designed a framework that compares different segmentation methods like watershed, threshold, k means clustering, region seed, fuzzy C, and showed that Region seed growing algorithm was found to be the best image segmentation algorithm.

IV. Proposed method

To identify lung cancer nodules, we use image processing methods and convolutional neural networks (CNN).

We use image pre-processing to eliminate the noises that exist in the CT-scan images so that we can identify if there are any abnormal masses present in the lungs.

To minimize noise and improve contrast, the image is pre-processed with the Median, Gaussian filters, and Adaptive Histogram Equalization function. Thresholding and Watershed segmentation is then used to extract nodules present in the image.

Finally, CNN-Deep Learning architecture is utilized to extract numerous characteristics and spatial features of the image, as well as to categorize the identified nodules as malignant or benign.

V. Block Diagram

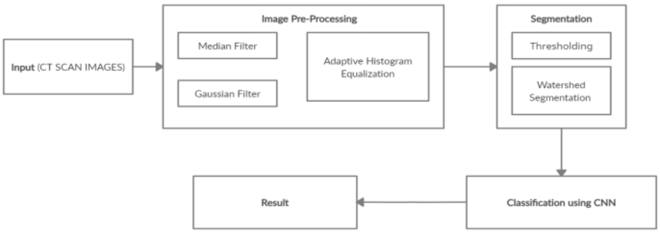

Fig 1 Block Diagram

VI. Image Preprocessing

A. Filters

There are three types of noises present in CT scan images, Gaussian, Salt and Pepper noises. To reduce these noises, we used Median filter, Gaussian filter, and Adaptive Histogram Equalization function. Median Filter is a non-linear filter used to especially remove outliers from an image. We employed it to remove the salt and pepper noise. Gaussian Filter is a low pass filter used to remove the gaussian noise, it smoothens the image by convolving with the gaussian function, removing the high frequency components. Adaptive Histogram Equalization is used to enhance the edges in each section of an image and to improve the overall local contrast.

B. Segmentation

We use Thresholding and Watershed segmentation techniques to segment out the nodules in the image. Thresholding technique is based on having a threshold value to convert a gray-scale image into a binary image. In this technique image is segmented by comparing pixel values with a predefined threshold limit L. Watershed Segmentation is used to detect and separate out touching/overlapping objects in images which will help in segmenting the nodules.

VII. Convolutional Neural Networks

A. Data Augmentation

Data augmentation is a technique used to increase a dataset by modifying existing images using methods like rotating, scaling, flipping, and shearing to generate a greater number of images. Different combinations of augmentation techniques were used with the original dataset to increase the size of our dataset from 100 images to 1400 images.

B. CNN

A Convolutional Neural Network is a deep learning algorithm which can take in an input image, assign importance (learnable weights and biases) to various aspects/objects in the image and be able to differentiate one from the other.

CNN architecture comprises the following layers:

- Input Layer: The input layer takes input data which are 3-dimensional images with shape as Width x Height x Depth and by default the depth parameter is set to 3 which means that it's an RGB image. The input layer consists of input neurons that contain the input data (the entire dataset for the CNN) which are connected to the next layer of CNN i.e. the convolution layers.
- Convolution Layer: Convolutional layers apply convolution to the input and transfer the output through to the network's subsequent layers. A convolutional layer's sole purpose is to detect image features such as lines, edges, colour drops, etc. The convolution layer contains convolution filters that sweep out features from an image i.e., it tries to learn from an image. The depth of the filter/kernel is equal to the depth of the image.
- Pooling Layer: The pooling layer is commonly used to shrink the activation map's spatial size. Not only does it reduce the amount of computation required, but it also protects the model from overfitting. It summarizes the characteristics found in a region of the feature map produced by a convolution layer and simplifies the information collected by the previous layer.
- Fully Connected Layer: Fully connected layers are the ones that perform discriminative learning in deep neural networks. It is a multi-layer perceptron that learns weights, identifies, and classifies an object class. Fully Connected Layer is simply feed-forward neural networks. The output of the final

convolution and pooling layers has to be sent to the fully connected layers.

- Output Layer: A CNN's output layer is the final fully connected layer, with the number of units/perceptrons/neurons equal to the number of classes defined or trained on. The final layer employs the softmax activation function, which aids in the solution of multi-class classification problems.

VIII. PROPOSED ARCHITECTURE

We used 8 convolutional layers and 4 fully connected layers with max pooling, batch normalization, and dropout layers for our proposed model.

We used 2 convolution layers having 384 and 256 filters with filter size of 1x1 to retain the feature map sizes as they would be decreasing when sent to the subsequent layers which would lead to lesser features being learnt by the subsequent layers. We used dropout layers between convolution layers and also in between the fully connected layers in order to avoid the model from overfitting during training with 0.7 dropout rate.

We used 8 convolution layers with decreasing filter sizes like 11x11, 5x5, 3x3, 1x1 and an increasing number of filters in each layer like 96, 256, 384, 512 to achieve higher accuracy and to improve the learning process in training. We used 3 convolution layers in series - twice, to extract higher level features in each iteration.

We used Batch Normalization layers after each convolution layer in order to normalize the inputs to the next layers to overcome Internal Covariate Shift (ICS) and to accelerate the training.

Max Pooling was used as the pooling technique to reduce the feature map size and to represent the features learnt by the previous layers in a condensed form. We used 3 Fully connected layers with 4096 neurons with the inputs from the previous layer linked to every neuron of the next layer. It is used to perform discriminative learning. The last Fully connected layer with 2 output neurons is used to classify the output as benign or malignant.

We performed hyperparameter tuning by tuning parameters such as kernel size, number of filters, batch size, number of epochs, padding, stride and making use of early stopping in order to improve the performance of the model and to get better accuracy

IX. RESULTS

A. Segmentation

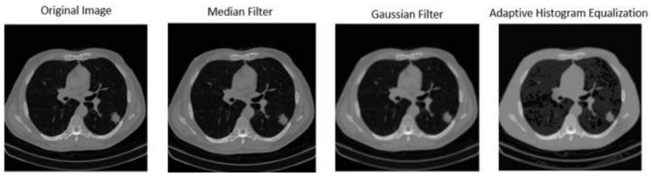

Fig 2 outputs after preprocessing with various filters

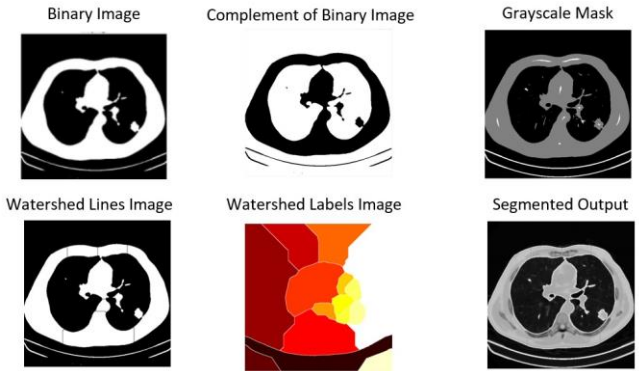

Fig 3 outputs of segmentation algorithms

B. Proposed Model

Plots for model accuracy and model loss vs number of epochs is plotted and score is generated using test dataset. Number of wrong predictions and classification report are also generated.

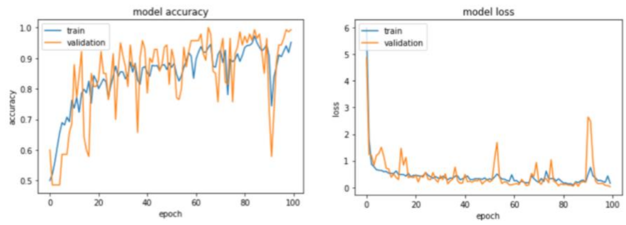

Fig 4 model accuracy and model loss

```
score:  [0.02355821058154106, 0.9928571581840515]
Wrong predictions:  1
              precision    recall  f1-score   support

           0       0.98      1.00      0.99        65
           1       1.00      0.99      0.99        75

    accuracy                           0.99       140
   macro avg       0.99      0.99      0.99       140
weighted avg       0.99      0.99      0.99       140
```

Fig 5 score and classification report

C. *Comparison Analysis*

We compared evaluation metrics of different CNN architectures with our proposed model.

TABLE 1. Comparison Analysis

Model	Accuracy	Precision	Recall	F1 Score	Train Loss	Validat-ion Loss
LeNet	88.57	0.87	0.88	0.88	~0	0.9127
AlexNet	89.99	0.90	0.90	0.90	0.2752	0.9657
VGG16	51.43	0.23	0.50	0.32	0.6931	0.6930
Proposed Model	99.28	0.99	0.99	0.99	0.1812	0.0235

X. CONCLUSION

We developed a lung cancer detection model based on CNN-Deep Learning architecture and could classify the detected nodules as either malignant or benign.

Achieved higher accuracy (99.28%) and performance with the use of image processing techniques and proposed CNN model when compared to other architectures and models we came across during literature survey.

REFERENCES

[1] Suren Makajua, P.W.C. Prasad, Abeer Alsadoon, A. K. Singh, A. Elchouemi, “Lung Cancer Detection using CT Scan Images”, 6th International Conference on Smart Computing and Communications, 2018.

[2] K.Mohanambal , Y.Nirosha , E.Oliviya Roshini , S.Punitha , M.Shamini, “Lung Cancer Detection Using Machine Learning Techniques”, International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering, Vol. 8, Issue 2, February 2019.

[3] Jeyaprakash Vasanth Wason and Ayyappan Nagarajan, “Image processing techniques for analyzing CT scan images towards the early detection of lung cancer”, Biomedical Informatics, Department of Computer Applications, Alagappa University, September 12, 2019.

[4] Ibrahim M. Nasser, Samy S. Abu-Naser, “Lung Cancer Detection Using Artificial Neural Network”, Department of Information Technology, Faculty of Engineering and Information Technology, Al-Azhar University-Gaza, Palestine 2018.

[5] Margarita Kirienko,1 Martina Sollini,1,2 Giorgia Silvestri,3 Serena Mognetti,3 Emanuele Voulaz,4 Lidija Antunovic,2 Alexia Rossi,1,5 Luca Antiga,3 and Arturo Chit, Convolutional Neural Networks Promising in Lung Cancer T-Parameter Assessment on Baseline FDG-PET/CT, 2019.

[6] Vaishnavi. D, Arya. K. S, Devi Abirami. T, M. N. Kavitha, “Lung Cancer Detection Using Machine Learning”, INTERNATIONAL JOURNAL OF ENGINEERING RESEARCH & TECHNOLOGY, VOLUME 7, ISSUE 01, 2019

[7] K.Narmada,G. Prabakaran,”An Effective Lung Cancer Detection And Classification Using Enhanced Fully Convolutional Neural Networks”,INTERNATIONAL JOURNAL OF SCIENTIFIC & TECHNOLOGY RESEARCH VOLUME 9, ISSUE 01, JANUARY 2020

[8] Ashok Kumar Yadav, Ramnaresh, Kamaldeep Joshi, Robin Singh, Shagun Rana, Ashish Krishan, Ritika Sharma,”Lung Cancer Detection by using Adam Algorithm and Convolutional Neural Network”,International Journal of Engineering, Applied and Management Sciences Paradigms,2019

[9] Ibtihal D. Mustafa, Mawia A. Hassan,”A Comparison between Different Segmentation Techniques used in Medical Imaging”,American Journal of Biomedical Engineering 2016, 6(2): 59-69 DOI: 10.5923/j.ajbe.20160602.03

[10] Asifullah Khan, Anabia Sohail1, Umme Zahoora1, and Aqsa Saeed Qureshi1” A Survey of the Recent Architectures of Deep Convolutional Neural Networks”,Published in Artificial Intelligence Review, DOI: https://doi.org/10.1007/s10462-020-09825-6