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Detection of Lung Diseases Using Deep Learning

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***Abstract*— Cancer is a very common disease type in worldwide. There are many types of cancer. Lung cancer is the most common type of cancer. Lung cancer which is common in both men and women can be fatal. The initiation of treatment by diagnosing cancer is important in reducing the risk of death. In this paper, classification of lung nodules is performs using CT images of SPIE-AAPM-LungX data. Deep learning has been a popular choice for the classification process in recent years. Especially it is used in the implementation of tensorFlow and 3D convolutional neural network architecture from deep learning libraries.**

***Index Terms*—Lung cancer, Deep learning, ResNet, image classification.**

I. Introduction

Cases that are natural and intuitive for humans, such as recognition and discrimination that are the result of perceptions such as sight and hearing, are challenging problems for machines. The artificial intelligence, which is aimed at ensuring the success of the machines in such problems, is improving day by day. One of the big steps in the history of artificial intelligence is the finding of artificial neural networks. Artificial neural networks have been satisfying for many years. They have not been able to meet the demands of the commercial field especially with advancing technology [1]. At this point, multilayered structures called "Deep Learning" have been emerged.

Deep learning from machine learning techniques has been very popular lately. The state-of-the-art technology is achieving solutions to many problems such as image processing, signal processing and natural language processing [2].

Biomedical image classification is the area where deep learning is common used. The field of biomedical image classification has been attracting interest for many years. There are many methods used to detect diseases. Disease detection is often preferred by looking at tomography images.

Early diagnosis of the disease leading to death is very important. One of the tools used to diagnose the disease is computerized tomography.

Nodules in the lung are classified as benign and malignant. Malignant nodules indicate that the patient is cancerous, whereas benign nodules indicate a non-cancerous patient [3].

There are many studies in the literature for lung cancer detection.

T. N. Shewaye et al. [4] proposed an automated system for classifying lung nodules as benign and malignant in CT images. In the system, geometric and histogram have used a combination of lung nodule image features and different linear and nonlinear separators. J.Cabrera et al. [5] performed lung cancer classification using microarray data and SVM. R. Nurtiyasari et al. [6] used wavelet and KNN.

A. M. Suzan et al. [7] used the bag of feature approach to classify good and bad tumors in the lung. In this approach, SIFT is used for feature extraction, and these coefficients are specified using a feature bag to a predefined codebook. This code book is given as an introduction to the KNN classifier. The system was evaluated with Area under the curve (Auc).

R. Anirudh et al. [8] employed three-dimensional CNN architecture to detect the lung nodule. Performance evaluation was done with SPIE-LUNGx data.

Q. Song et al. [9] utilized three separate neural network architectures for cancer classification. These architectures were tested on the same basis and the results were evaluated.

S. M. Salaken et al. [10], a new piece of information using CNN to detect lung nodules. Supported detection system. In studies using data enhancement techniques, nodule candidates in the form of 3D cubes are fed with CNN trained to separate nodules and non-nodular inputs.

M. F. Sergece et al. [11] used deep learning for lung cancer diagnosis. They have proposed a new network of convolutional neural networks to increase the accuracy of the diagnosis. In addition, some approaches suggested in the Kaggle competition have compared.

Although studies in the literature have been made using many different machine learning algorithms, recently deep learning have preferred by academic and science environment because of its success.

In the study, binary classification of the lung nodule is performed, emphasizing the early diagnose of lung cancer. Convolutional neural networks are preferred for processing. It is used during the implementation of the tensorflow [12] method, which is one of the popular libraries. Training and testing procedures are shown using SPIE-AAPM [13] dataset.

The structure of this study is as follows; section 2 describe structure of CNN. Section 3 describes the proposed method. Finally, the section 4 defines the results of the study.

II. CONVOLUTIONAL NEURAL NETWORK

Deep learning almost succeeds in every field where is applied. Convolutional neural networks, one of the deep learning architectures, are most likely to solve image classification problems.

Convolutional neural networks attract attention and become popular because ImageNet [14], an annual image classification competition, has significantly increased the success rate in 2012 compared to previous results using a convolutional neural network. In the years following the competition after 2012, the vast majority of participants have started using convolutional neural networks.

Convolutional neural networks (CNN) are multi-layered structures. CNN is a feed forward and very effective method especially in detecting. Network structure is simple; has less training parameters. CNN is more like biological neural networks thanks to its weight-sharing network structure. However, the complexity of the network model and the number of weights are reduced. In the structure of the network, there are layers named as Convolution, Activation, Pooling and fully connected layer. CNN has a loss function, such as softmax, in the final layer, as in traditional neural networks [15].

Traditional neural networks contain trainable weights, the contained layers are one-dimensional. Neurons in the layer are completely connected to neighboring neurons. Convolutional networks are similar in that they have trainable weights, but they are separated from traditional networks in that they have three dimensions and that neurons are not fully connected.

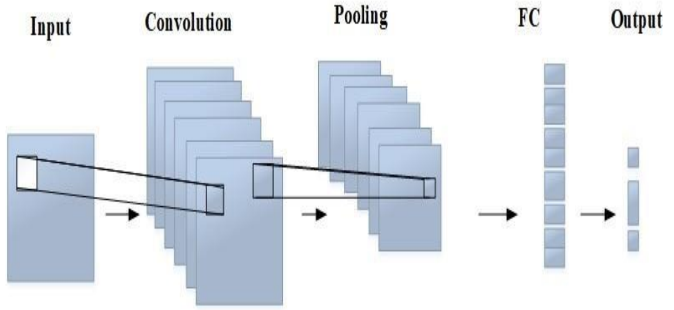

Fig.1. Structure of a CNN model

Fig.1 shows the structure of a traditional convolutional neural network. The given network consists of input, pooling, convolution, fully connected layer and output layers. Convolutional neural networks are consists of many parts. While the convolution layer is successful in extracting features, the pooling layer is used to enlarge or reduce the image size. In some CNN networking models, the pool layer is replaced by sub-sampling layers. The activation layers are usually followed by an activation layer. The fully connected layer is connected to all the neurons in the previous layer and is used to classify the extracted features into various classes based on the training dataset [16]. The final layer of convolutional neural networks can perform an ultra-specific classification by combining all the specific features extracted from the input data in the previous layers.

III. PROPOSED METHOD

In the proposed method, tensorflow library is used for performing the lung cancer diagnosis procedure. Tensorflow is preferred for its ease of use and flexibility. The SPIE-AAPM-LungX [13] database is used for the classification of lung cancer nodule, which is organized as part of the SPIE conference in 2015. The dataset contains CT images of 70 patients. The images of 10 patients in the dataset is uses for training. The images of 60 patients in the dataset is uses for training too. For system training, 3D convolution neural network architecture is utilized. The flowchart of the proposed method is as shown in fig.2.

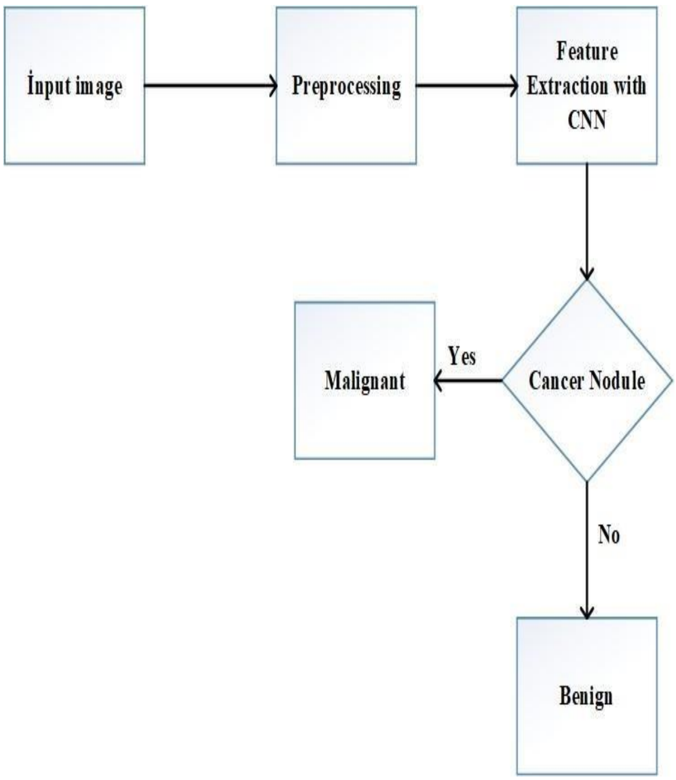

Fig.2. Flowchart of the system

A. 3D Convolutional Neural Network

In the proposed method, 3D network architecture is used. The main difference between 3D CNN and 2D CNN is the convolution process [17]. The input layer is a 4D tensor. It consists of depth, height, width and channel parameters. Here an additional dimension called "depth" is added. When the filter is covered in the input layer, it moves in 3 dimensions. A filter also contains weights and bias sets. Applying them to the

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input layer creates a new 3D cuboid. Fig.3. gives a 3D convolution.

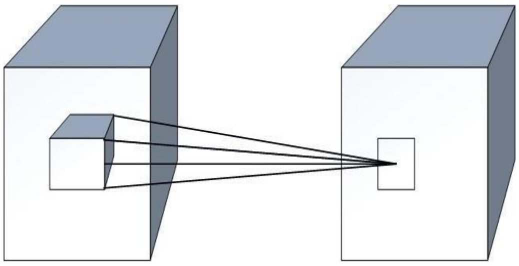

Fig.3. 3D Convolution

At the end of many filters a new 4D tensor is produced ready for the next 3D convolution. 3D pooling is similar to 2D pooling. We reduce the dimensions in the first 3 dimensions and we remove them without changing the channel. Adding a new dimension brings some situations together. Since the depth is a new multiplier, the actual size of each dimension cannot be too great. The width and height dimensions of the applied architecture are determined as 50 and the depth is 20.

As the number of layers in the used network increases, the success of the method improves. However, as the network depth increases, the problem becomes unity and the network becomes corrupted [18]. Therefore, the number of layers is not increased much. The architecture used is given on the table.1.

TABLE I. STRUCTURE OF CNN

Layer1	Input(50x50x20)
Layer2	Conv1+relu+pool
Layer3	Conv2+pool
Layer4	Conv3+pool
Layer5	Cov4+pool
Layer6	Conv5
Layer7	Fully Connected

B. Dataset

There are public databases available for diagnosis of lung cancer. The most frequently used data from these datasets is the LIDC-IDRI dataset [19]. Dataset consists of lung cancer screening and computerized tomography scans. Seven academic centers and eight medical imaging companies collaborated to create a database of 1018 cases. In addition, competitions are organized to increase the accuracy of classification. One of these competitions is the SPIE-AAPM Lung CT Challenge held in 2015.

The SPIE-AAPM Lung Challenge was organized as part of the SPIE Medial Image Conference with the support of American Association of Physicists in Medicine (AAPM) and the National Cancer Institute. In order to classify the lung nodules as malignant or benign, the use of a common dataset is presented to more accurately evaluate the competitors.

In our study, SPIE-AAPM dataset is used. Dataset contains CT images of 70 patients. 10 of the cases are reserved for training and the remaining 70 are reserved for testing. In our practice, 40 of these data are used for training and 30 are used for testing. Fig.4. gives some images are taken from the dataset.

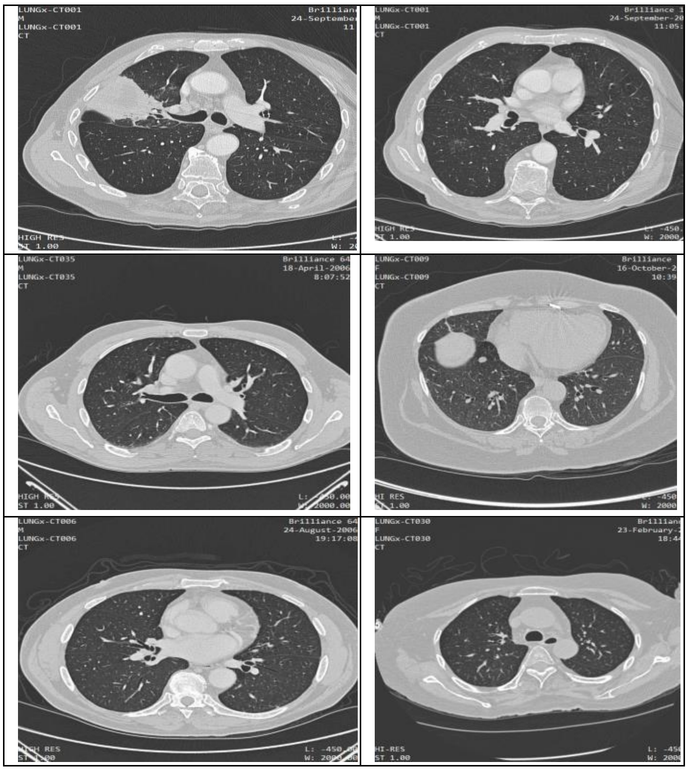

Fig.4. Some CT Scans in SPIE-AAPM dataset

C. Experimantal Results

The dataset used is composed of many CT images of the patient in DICOM format. Each image includes a series with multiple axial slices of the chest cavity and a different number of 2D slices. The microdicom file viewer is used to view images in DICOM format. Microdicom allows you to convert dicom format images to .png, bmp and jpg format. First, the classification is tried by converting the images to png format, but the accuracy is not satisfactory because of the data loss.

We uses the pydicom package in the Spyder environment using python language to work with dicom format images.

When evaluating the performance of the classification process, several metrics are used. The performance evaluation of our binary classification process is realized with the confusion matrix.

Confusion matrix: One of the simplest and most intuitive metrics used to find the model's accuracy [20]. The accuracy is determined by looking at the TN, TP, FP and FN numbers in the model.

TN: The actual class of the data is false and the estimate is false

TP: The actual class of the data is true and the estimate is true

FP: The actual class of the data is false and the estimate is true.

FN: The actual class of the report is true and the estimate is false

30 cases are used when the method is evaluated. Of these patients, 17 are malignant (true) and 13 are benign (false). The confusion matrix of the results of this training is shown in table 2 and fig.5. after the testing of the trained model.

TABLE II. CONFUSION MATRIX OF SYSTEM

TP =12	FP=4
FN=5	TN=9

Accuracy of model is computed as %70 with this formula:
Accuracy= (TP+TN)/ (TN+TP+FP+FN)
= (12+9)/(12+9+4+5)
= 0.7

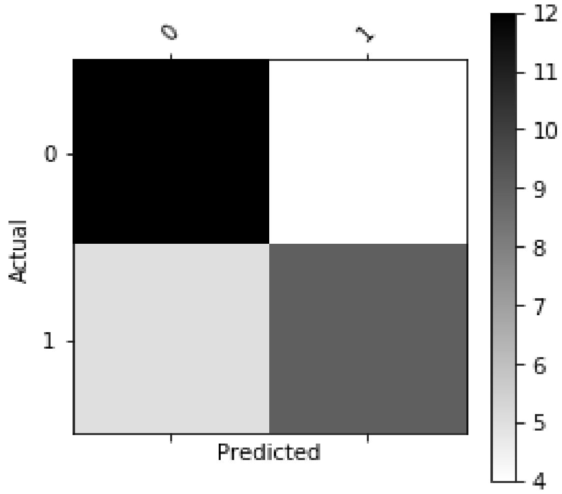

Fig.5. Confusion matrix of model after test process

IV. CONCLUSION

This study draws attention to the early diagnosis of lung cancer. Lung nodule classification is benign and malignant. Deep learning architecture CNN is especially known for its success in image classification. For biomedical image classification operation, it also obtains successful results. 3D CNN architecture is used for classification in the study. Experimental results show that the method is successful, although the images in the data set used are rather small. In the future, the performance of the system can be improved with a larger dataset and an improved architecture.

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