DEEP CONVOLUTIONAL NEURAL NETWORKS TO DETECT LUNG CANCER STAGE

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***Abstract*—**Regardless of the type of cancer, the treatment process starts after the staging process. The treatment method to be applied to the cancer patient depends on the stage of the disease. Therefore, all studies on the staging of cancer types have a big precaution. In this study, deep convolutional neural networks (DCNN) were used for staging of lung cancer. The TNM classification system is considered for staging. According to TNM, there are nine tumor stages in lung cancer. In the study, 200 data for each stage of lung cancer and 1800 MR images for 9 stages in total were used. As a result, a classification of 99.8% accuracy was performed in order to stage lung cancer with the proposed DCNN model.

Keywords*—*Deep learning, Convolutional neural network, Lung cancer, Stage

I. INTRODUCTION

LUNG Cancer is one of the most common cancer types in the world. It constitutes about one third of all cancer deaths. Only 15% of all lung cancers survive 5 years and more after diagnosis [1]. However, in the early stages this rate is quite high. It is necessary to know the stage of the disease for selection of treatment and prognosis in lung cancer. Clinical features, biochemical tests and radiographies of the patients are evaluated and stage determination is done by the staging methods. Pathologic examination is needed to classify lung cancer, to determine the level of invasion and to determine the surgical margins of the cancer [2,3]. Lung cancer is in 4 main stages. Computed tomography or magnetic resonance imaging for the abdomen or brain, bone scan (whole-body bone scintigraphy), PET, etc. are performed to determine the correct stage [4]. Some limited surgical interventions may be required to ensure complete staging.

Convolutional neural networks can be regarded as the most advanced state of machine learning approaches in recent years. There are many applications in the literature where convolutional neural networks are used. Conventional neural networks are used to solve image processing, medical image analysis and segmentation as well as classification and identification problems. Models in which the number of data and hidden layers are used much more are considered as deep learning approaches [5-8].

This study also used a convolutional neural network model that may be important in deciding on the treatment of lung cancer and may help to staging cancer. The study will shed light on the subsequent staging studies.

In the study, only the primary tumor part of the TNM staging system is based.

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II. MATERIALS AND METHODS

This study was based on the 'primary tumor' category in the 'Tumor Staging System' (TNM) classification. 9 stages were selected as DCNN output. The TNM Staging System is based on the extent of tumor (T), the extent of spread to lymph nodes (N), and the presence of metastasis (M).

Table I. TNM staging [9-11]

	Primary tumor (T)
Tx	No primary tumor detected
T0	No evidence of primary tumor
T1	Tumor keeps lamina propria, muscularis mucosa or submucosa
T1a	Tumor keeps lamina propria or muscularis mucosa
T1b	Tumor keeps submucosal
T2	Tumor keeps muskularis propriayı
T2a	Tumor subserosa retained, visceral peritoneum, no adjacent organ involvement
T2b	The tumor keeps the serosa (visceral peritoneum) and neighboring organs.
T3	The tumor keeps the serosa (visceral peritoneum)
T4	Tumor keeps neighboring organs

Table 1 shows the primary tumor part of the TNM classification. In the TNM classification, the 'T0' state shown in Table 1 was excluded when only the tumor condition was considered [9 -11]. Therefore, with the proposed DCNN model, the remaining 9 stages were tried to be estimated except the T0 in the staging system in Table 1.

The data set used in the study was obtained from the Cancer Imaging Archive (TCIA) website [12- 14]. In the study, 200 data were selected for each stage from image data of 5600 lung cancers and a data set consisting of 1800 data sets for 9 stages in total was used. In Figure 1, 1800 data from lung cancer patients in the dataset are randomly selected and presented as an example. The actual size of the images in the data set is 512x512 and consists of three channels and black and white colors in different tones. All image data is reduced to a size of 250 x 250 pixels for the model training period to be short. The sample dataset of 250 x 250 size consisting of random 36 data is shown in figure 2.

III. METHODOLOGY

In this study, a convolutional neural network model, which is accepted as the basic tool for deep learning, has been used [15]. The image data is automatically labeled according to folder names. This is done using the "imagedatastore" function in the MATLAB environment. The "imagedatastore" function also helps to efficiently read image stacks during storage of large image data, including data that does not fit in memory, and training of the deep convolutional neural network [16]. The original size of the image data used in the study is 512x512x3. Image data is reduced to the 250x250 size for 3 channels. There is no specific reason for choosing 250 pixels. A different dimension of 250 x 250 could be chosen, but in this case the training duration of the model will also change. In the study 200 data were used for each stage. A total of 1800 data were used for 9 phases. In the study, the data set is divided into two for each label. For each label, 75% of the data is allocated for training of the model. Thus, 150 data for each label were used in the training and the remaining 50 data were used in the test. The maximum epoch 30 and initial learning rate 0.0001 were selected as training options. Figure 3 shows the proposed DCNN model.

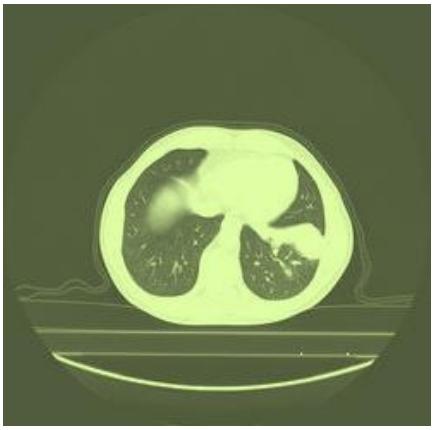

Fig. 1. MR image sample of lung cancer

The following layers are used in the DCNN model:

Input layer: At the input layer, the real image data is reduced to 250 x 250 and presented to the next layer, the convolutional layer.

Convolution layer: In the convolution layer, it is very important that the training function uses the size of the filter and how many it is used when scanning. Three convolution layers were

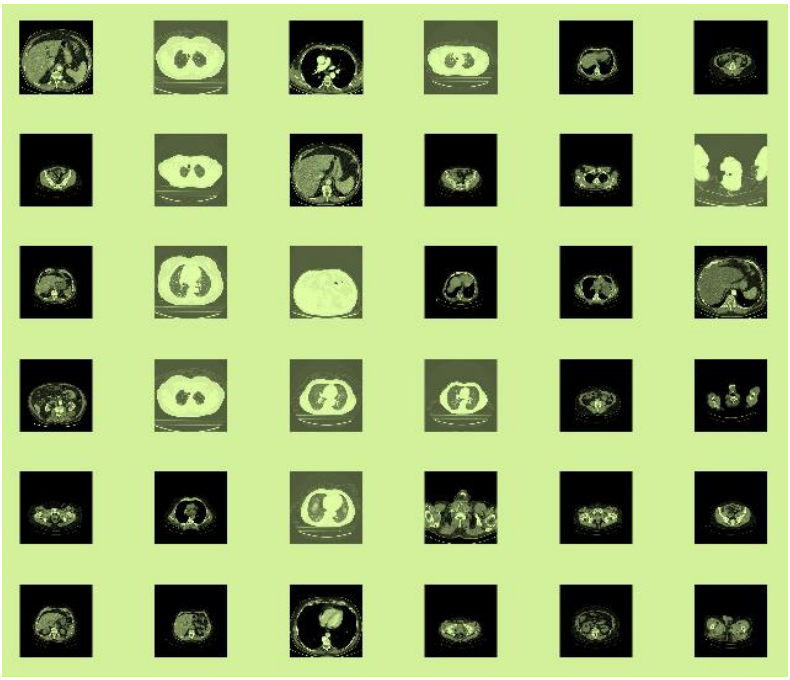

Fig. 2. Randomly selected sample dataset from real dataset

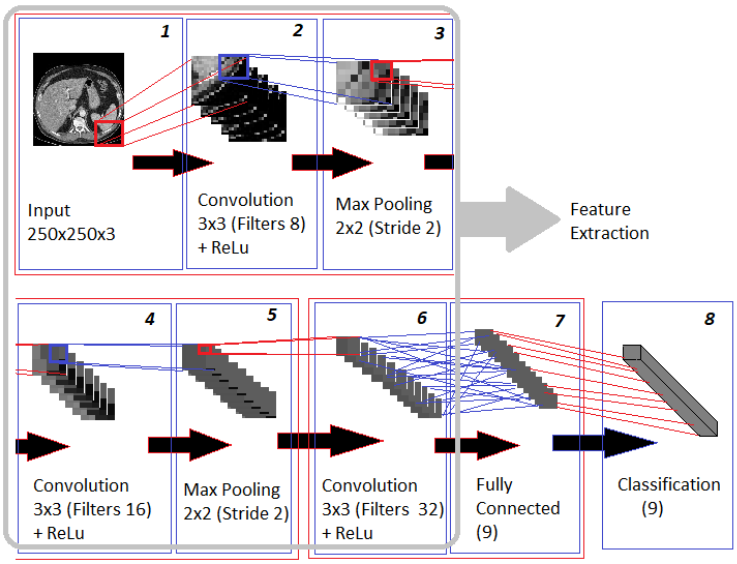

Fıg. 3. Proposed DCNN model

used in this study. As shown in Fig. 3, in the convolutional layer used in section 2, 8 filters of 3 x 3 dimensions are used. In the convolution layer used in section 4, 16 filters were used in the same dimension and 32 filters were used in the convolution layer in section 6. The number of filters specifies the number of feature maps [16, 17].

ReLu layer: The nonlinear activation function follows the convolution layer. Since the study was performed in MATLAB environment, "rectified linear unit function" (ReLU) was chosen as the activation function.

Max-pooling layer: There is a max-pooling layer (along with the activation function) after the convolution layer, as a way of preventing the model's memorization and at the same time reducing the number of model parameters. In the 'Max-pooling' process, a rectangular frame is strided step-by-step over the entire view of the convolution layer. For each stride, the maximum number of numeric values on the image is taken. The rectangular frame is chosen as 2x2 and 2 squares in the 3 and 5 divisions [16-18], as can be understood from figure 3.

Fully connected layer: Usually one or two fully connected layers are used after the convolution layers. One ‘fully connected layer’ was used in the study. All neurons in the 'Fully connected layer' are connected to neurons in the previous layer. This layer combines all of the features (local information) learned by previous layers to define larger patterns. For this reason, the "OutputSize" parameter in the last fully connected layer is equal to the number of classes in the target data. In this study, the output size is 9, corresponding to 9 stages. The 'softmax' activation function is used to classify at the fully connected layer [16-18].

Classification layer: Last layer. This layer uses the probabilities produced by the softmax activation function for each input to mutually assign them to specific classes [16-18]

IV. RESULTS

As a result of the test made, the accuracy rate for classification was 0.9889. Table 1 shows the training process of the model. As shown in Table 1, 100% mini batc accuracy was obtained at 410.14 seconds in the 30th epoch. And at the 30th epoch, the minibusc loss is very close to zero with 0.0112.

Table II. Training process of the DCNN model

Epoch	Iteration	Time Elapsed (seconds)	Mini-batch Loss	Mini-batch Accuracy (%)
1	1	15.63	2.1997	7.81
5	50	84.57	2.1809	24.22
10	100	147.85	1.8129	25.78
15	150	211.38	0.836	72.66
20	200	276.42	0.1005	97.66
25	250	343.48	0.1028	99.22
30	300	410.14	0.0112	100.00

The graph in Figure 4 gives the error of the testing process. In Figure 5, the accuracy of the model is given in the testing process.

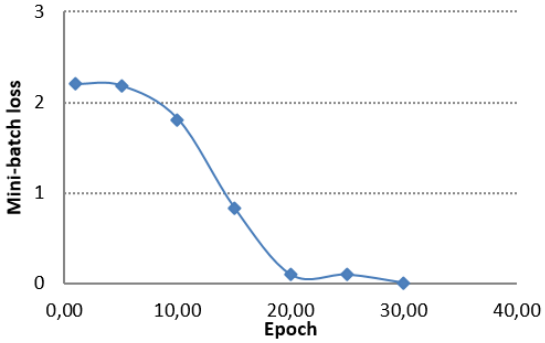

Fig. 4. Mini-batch loss for testing

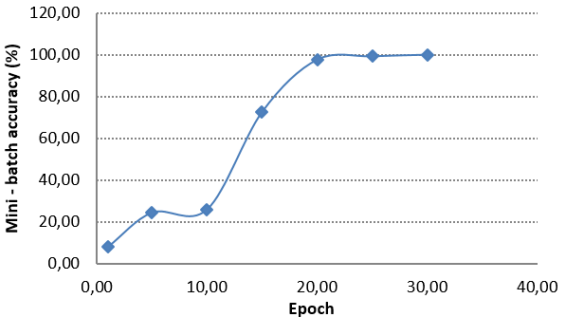

Fig. 5. Mini – batch accuracy for testing

V. CONCLUSIONS

The real size of the images used for the data set in the study is 512x512. For training and testing of the proposed DCNN model, the image data in the data set is reduced to 250x250 pixels in the first phase. Normally, in simple classifications, much lower data is used. For example, image classification is often used 28 x 28. However, the estimation and / or classification of the stage of lung cancer is an extremely sensitive issue, so the picture size has not been reduced much. The goal is to achieve a very high accuracy rate. The 30 epoch limit can be thought of as too much. As a result, as Table 2 reveals, the thirtieth epoch was reached at the end of 410.14 seconds. This duration seems to be longer than normal, but the accuracy rate of 0.9948 is quite satisfactory. In the last epoch, the lowest error rate was obtained, quite close to zero. This study has produced very successful results in terms of shedding light on more extensive studies in the future for staging other cancer types or including other staging categories.

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