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# Diagnosis of Lung Cancer Based on CT Scans Using CNN

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## ABSTRACT

Lung cancer is one of the most lethal cancer types; thousands of peoples are infected with this type of cancer, and if they do not discover it in the early stages of the disease, then the chance of surviving of the patient will be very poor. For the suggested reasons above and to help in overcoming this terrible, early diagnosis with the assistance of artificial intelligence procedures most needed. Through this research, a Computer-aided system introduced for detecting lung cancer in a dataset collected from the Iraqi hospitals by using a convolutional neural network technique with AlexNet architecture for helping with the diagnosis of the patient's cases: normal, benign, or malignant. The proposed model gives high accuracy ups to 93.548%. The other performance metrics comes with high values such as 95.714% for sensitivity and 95% for Specificity.

**Key words:** lung cancer, Convolutional neural network, CAD System, Artificial intelligence

## 1. INTRODUCTION

Lung cancer is one of the most well-known life-threatening illnesses in the globe(1). The up-to-date estimations are given by the "World Health Organization" (WHO) say that approximately 7.6 million mortality worldwide every year because of lung cancer. Furthermore, mortality due to this type of cancer is assumed to continue growing, to become almost 17 million worldwide in 2030(2, 3).

According to the statistics of "The American cancer society", lung cancer is the head cancer killer in people in the United States.(4) The overall number of the estimated new cases of all types of cancer in 2013 was 1660290 (854790 for men and 805500 for women), the number of lung cancer was 228199 incidences (118080 for men and 110110 for women). Where the total number of estimated death cases of cancer are 580350 cases (306920 for men and 273430 for women), in the case of the lung cancer the number of death cases was 159480(87260 for men and 732220 for women)(5).

According to the Iraqi ministry of health in 2016, lung cancer is the second most widespread cancer type in Iraq. There are 2123 people who have lung cancer from two genders. This number represents about 8.31% of the total infections in the country. This portion indicates a small increase as compared to the ratio of the past year, which is about 8.1%. The rate of lung cancer represents approximately 13.27% of the total cancer cases, and this shows that lung cancer is the leading type in males. Also, there is a rise when compares to the ratio recorded in 2015, which approximately reaches 12.7%.(6, 7). For females, lung cancer not the leading cancer type, it ranked fifth between



other cancer types, in 2016 there is only 638 woman who has this disease, there are 638 women who diagnosed with lung cancer at 2016, this represents about 4.44% from the total cancer types infections. There is a slight rise if compared with the previous year, which represents approximately about 4.2%.(6, 7)

Cancer is the fourth cause of death in the eastern Mediterranean region and is the third cause of mortality in Iraq, and this rate is growing continuously. The chief and most notable of this raise is smoking. Other factors include pollution, unhealthy diet, endless exposure to manufacturing and agricultural carcinogens, and lowered physical motion(6). Total cancer mortality in Iraq in 2014 is (8211), approximately (4525) in males and (3959) in females. The most cancer sort deaths were the lung cancer with a total number of estimated deaths about (1339), (918) of them was for men and (421) of the total calculated estimate was for women, the entire portion of lung cancer mortality amongst all other kinds of malignancy was 16.31%. During 2016, the whole number of cancer losses fell to 7568 cases, where the most significant portion of them was lung cancer, approximately 1257, which implies a total percentage of 16.61% from the total predicted mortality(6, 7).

So for the reasons explained above, there is a necessity for implementing a CAD system for helping doctors in diagnosing lung cancer as possible as when in it is early stage, not only detecting the nodule but with high accuracy.

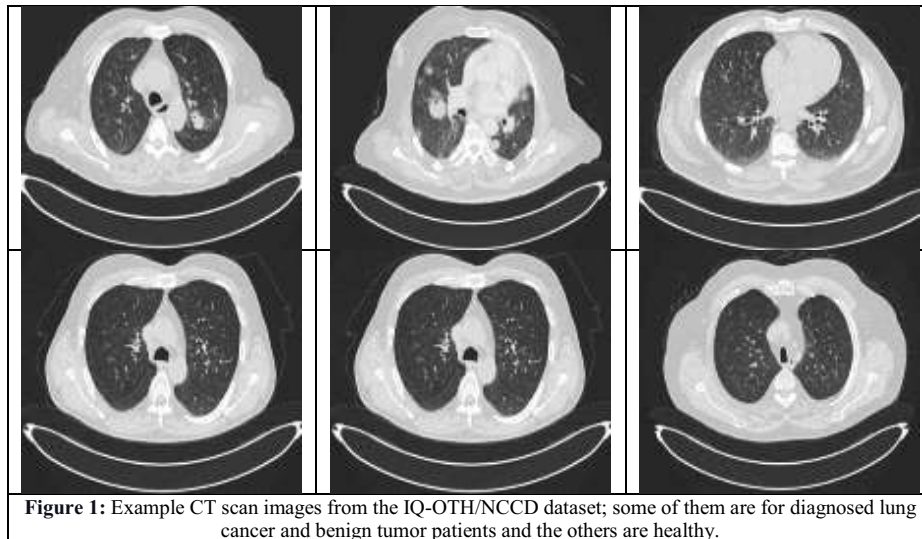
Several studies applied artificial intelligence techniques for this purpose, for examples: using artificial neural network for detecting lung cancer as in (8, 9), or using support vector machine technique as in (10-12), or applying K-nearest neighbor as in (13), or using genetic algorithm for this operation as in (14, 15), also, fuzzy techniques are efficient when using to detect lung cancer as in (16-18), convolutional neural network can be used for this purpose as in (19-21). Artificial intelligence not only used in the area of lung cancer diagnosing, but it applied in all fields of biomedical engineering such as: diagnosis of breast cancer in (22-24), diagnosis of Heart disease in (25-27), also diagnosing and classification of diabetes in (28).

In order to apply the above machine learning techniques, there is a need for using data as input to the algorithms which have been applied. Various methods are convenient for diagnosing lung cancer, particularly MRI, isotope, X-ray, and CT. X-ray chest radiography and Computer Tomography (CT) are the two well-known imaging modalities that are commonly utilized in the identification of different lung diseases(2, 29). In addition, there are many publicly databases used for the purposes of scientific research such as: ELCAP Public Lung Image Database, LIDC Database, and Data Science Bowl 2017.

The aim of our study is to implement a CAD system used as an assistant to doctors while deciding and diagnosing lung cancer, this system used for detecting and classifying the lung cancer cases if it normal, benign, or malignant with high accuracy. This done by applying convolutional neural network technique to a data set of lung cancer CT scans collected and diagnosed at the Iraqi hospitals.

## **2. The IQ-OTH/NCCD lung cancer dataset**

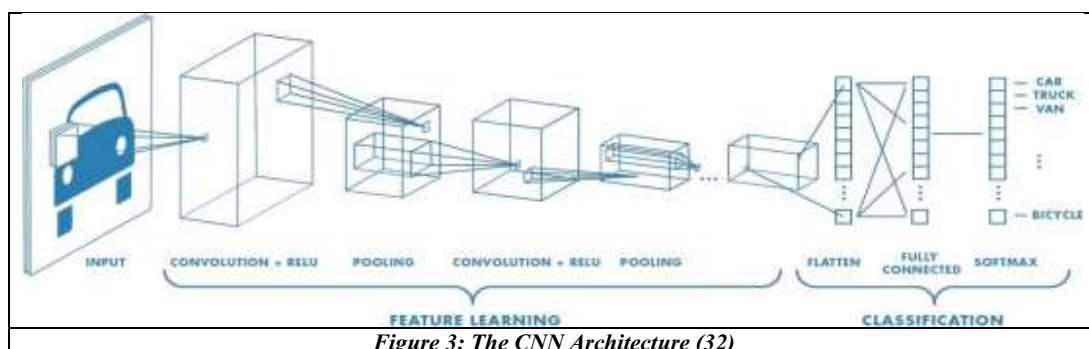
The Iraq-Oncology Teaching Hospital/National Center for Cancer Diseases (IQ-OTH/NCCD) lung cancer dataset was collected in the above-mentioned specialist hospitals over a period of three months in fall 2019. It includes CT scans of patients diagnosed with lung cancer in different stages, as well as healthy subjects. IQ-OTH/NCCD slide were annotated by oncologists and radiologists in the two centers. The dataset contains a total of 1190 images representing CT scans slices of 110 cases (see Figure 1). These cases are grouped into three classes: normal, benign, and malignant. of these, 40 cases are diagnosed as malignant; 15 cases diagnosed with benign; and 55 cases classified as normal cases. The CT scans are originally collected in DICOM format, each scan contains several slices. The number of these slices range from 80 to 200 slices, each of them represents an image of the human chest with different sides and angles. The 110 cases vary in gender, age, educational attainment, area of residence and living status. Some of them are employees of the Iraqi ministries of Transport and Oil, others are farmers and gainers. Most of them come from places in the middle region of Iraq, particularly, the provinces of Baghdad, Wasit, Diyala, Salahuddin, and Babylon. The dataset can be accessed online on Kaggle at (30)



**Figure 1:** Example CT scan images from the IQ-OTH/NCCD dataset; some of them are for diagnosed lung cancer and benign tumor patients and the others are healthy.

### 3. METHODOLOGY

In the proposed procedure, CNNs are applied to detect and classify lung cancer CT scans of the patients collected from hospitals. **Convolutional Neural Networks** is a sort of deep learning paradigm applied for processing data which has a grid pattern like images (31), it is all about using Deep Learning with Computer Vision. A good way to gain foreknowledge about this technique is to imagine a Neural Network Architecture also how it is practiced to visual tasks i.e. Video and Images. Furthermore, the Convolutional Neural Networks is an important technique used for Object Recognition, create Facial Recognition, Self-Driving Cars. A **Convolutional Neural Network** is a Deep Learning algorithm that can take in image as input, with assigning importance learnable weights and biases to various objects inside this image and be capable of differentiating one from the other. In addition, the pre-processing required for this technique is much lower if comparing with other classification algorithms. The role of the CNN is for reducing the images to a form that is easier to process but without losing features that are important for getting a good prediction (32). A typical CNN consists of three types of operation layers: the convolutional layer (CONV), the pooling layer (POOL), and finally the classifier layer (FC), as exemplified in the figure below.



**Figure 3:** The CNN Architecture (32)



The CONV layer performs the reading input feature maps or images from the previous layer when it used more than once, or from data input ports, then it transforms these inputs by many groups of kernels to a set of output feature maps. generally, Any CONV layer is usually following by a POOL layer which subsamples the features from the previous CONV layer. Finally, the classifier layer (FC) generates the possibility of each class implied at the initial input data(33). The **convolution layer** is an essential part in the structure of CNN, which responsible for extracting the features that typically consist of a mixture of linear "convolution operation" and nonlinear processes "**activation function**".

For the purpose of feature extraction operation in CNN, a convolution operation is a specific kind of the linear operations is responsible for doing this job, this done by applying a **kernel**, which a small-size array, crossed the **tensor**, which is also an array represents the input(34). The figure below shows how the computer sees an image by transforming it to an array of numbers:

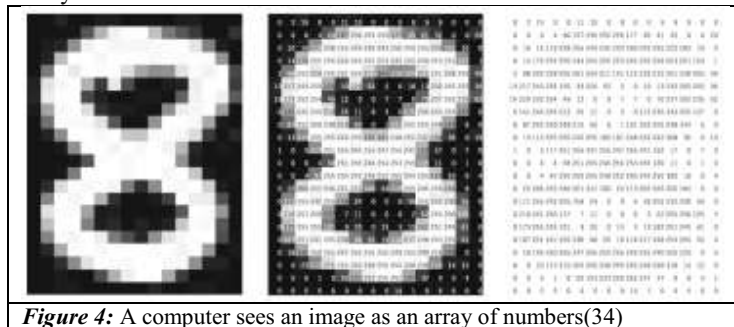


Figure 4: A computer sees an image as an array of numbers(34)

Then performing a calculation operation of element-wise product, at all locations, between all kernel elements and the tensor array, the resulting array from this operation represents the value of the output, named a **feature map**. The resulting feature map is reduced in width and height if compared to the input tensor, so there is a need for adding zeros at each tensor sides in order to keep the size of the input and the output the same, the mentioned above operation named Padding.

In contrast to padding operation, a process of reducing the dimensions of feature map known as **stride**, which represents interval separating every two consecutive kernel positions. Another procedure that achieves the same objective called a **pooling** operation. After convolution operation ends, the output from it passed into an activation function, like sigmoid, tangent, and ReLU, which is the typical popular nonlinear function(34).

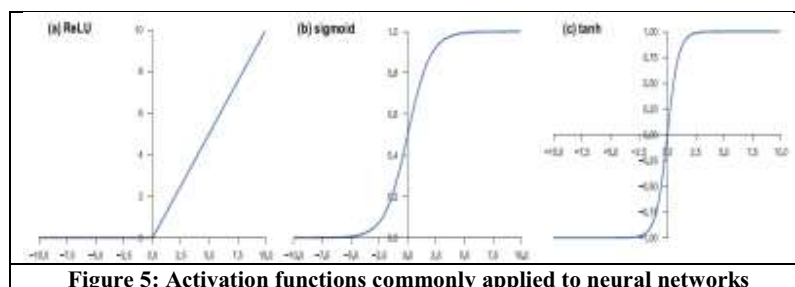


Figure 5: Activation functions commonly applied to neural networks

The convolution layer, followed by another layer named pooling layer, used in order to downsampling the size of the feature and minimizing the computational cost by choosing the maximum value of the feature map at a small area known as the pooling window(35).

An example describes the above explanation shown in the figure below, where a max-pooling operation is done:

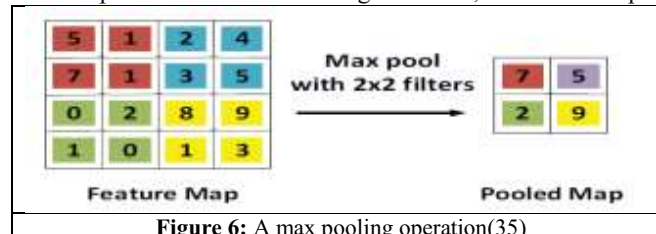


Figure 6: A max pooling operation(35)

The operation of transforming the resulting feature map to a one-dimensional array known as flattening, then this array will be connected to a dense layer, which is a fully connected layer. At the last layer, a particular activation

function was applied, which is differs from the other layers in the CNN; the commonly used type is softmax function(34).

### 3.1 The architecture of AlexNet

For the purpose of detecting lung cancer in CT scan we used in our study AlexNet(36) convolutional neural network:

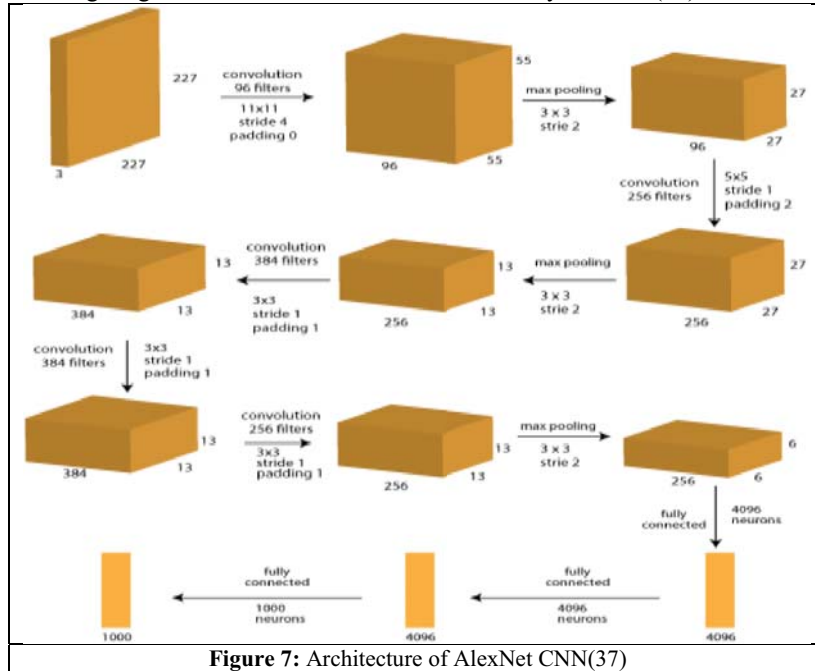


Figure 7: Architecture of AlexNet CNN(37)

1. Firstly, at the layer zero, which represents here the input image the size is  $227 \times 277 \times 3$ , which are respectively relates to height, width and depth.
2. Then a convolution process is done at the first layer with 96 filters and a size of  $11 \times 11$ , and the amount of stride is four, without padding, it mean the padding equals zero. Therefore, the result from this layer is an image with size of  $55 \times 55 \times 96$ .
3. At the second layer, a max-pooling operation follows the convolution process, this operation with a size of  $3 \times 3$  and a stride equals two, this gives a same depth filter that equals 96 with a size of  $27 \times 27$ , the depths being the same since this operation is performed on every layer independently.
4. At layer three, a convolution process with 256 filters and size of  $5 \times 5$  and stride equals 1 and padding equals 2 for the purpose of restoring the original size of  $27 \times 27$  but with a depth of 256(the filter size).
5. Again, Max pooling with a filter with a size of  $3 \times 3$  and stride 2 is performed, to downsampling the image size to  $13 \times 13 \times 256$ , also the depth is remain the same reason mentioned above.
6. At the layer five, the convolution operation is employed with a size of  $3 \times 3$ , and 384 filters, and here the stride and padding equals one, so the depth is increased to 384 and the size is remain the same.
7. Again, at the next layer, a convolution operation is done with the same size as the last convolution operation, and same stride and padding amount used, so the results are not changed.
8. At the seventh layer, a convolution operation is performed too. But with 256 filter and a size of  $3 \times 3$ , stride equals 1 and the same amount for the padding, therefore the results is as the same as the previous layer, but with a depth size of 256.
9. At layer 8, max pooling with a size of  $3 \times 3$ , and a stride equal 2, this yields an image with a size of  $6 \times 6$ , and a depth of 256.
10. The ninth layer, which is the fully connected layer, in this stage the previous resulted size  $6 \times 6 \times 256$  is multiplied for getting a 9216 pixels, this pixels will be fed into all 4096 neurons of AlexNet,
11. At the next layer the previous steps is repeated,
12. At last layer which is also a fully connected layer but with 1000 neurons.

The summary of the above network is described in the table below

Table 1- Summary of AlexNet CNN

Layer number	Layer name	Layer operation	Layer operation description
Layer 1	'data'	Image Input	227x227x3 images with 'zerocenter' normalization
Layer 2	'conv1'	Convolution	96 11x11x3 convolutions with stride [4 4] and padding [0 0 0 0]
Layer 2	'relu1'	ReLU	ReLU
Layer 2	'norm1'	Cross Channel Normalization	cross channel normalization with 5 channels per element
Layer 3	'pool1'	Max Pooling	3x3 max pooling with stride [2 2] and padding [0 0 0 0]
Layer 4	'conv2'	Grouped Convolution	2 groups of 128 5x5x48 convolutions with stride [1 1] and padding [2 2 2 2]
Layer 4	'relu2'	ReLU	ReLU
Layer 4	'norm2'	Cross Channel Normalization	cross channel normalization with 5 channels per element
Layer 5	'pool2'	Max Pooling	3x3 max pooling with stride [2 2] and padding [0 0 0 0]
Layer 6	'conv3'	Convolution	384 3x3x256 convolutions with stride [1 1] and padding [1 1 1 1]
Layer 6	'relu3'	ReLU	ReLU
Layer 7	'conv4'	Grouped Convolution	2 groups of 192 3x3x192 convolutions with stride [1 1] and padding [1 1 1 1]
Layer 7	'relu4'	ReLU	ReLU
Layer 8	'conv5'	Grouped Convolution	2 groups of 128 3x3x192 convolutions with stride [1 1] and padding [1 1 1 1]
Layer 8	'relu5'	ReLU	ReLU
Layer 9	'pool5'	Max Pooling	3x3 max pooling with stride [2 2] and padding [0 0 0 0]
Layer 10	'fc6'	Fully Connected	4096 fully connected layer
Layer 10	'relu6'	ReLU	ReLU
Layer 10	'drop6'	Dropout	50% dropout
Layer 11	'fc7'	Fully Connected	4096 fully connected layer
Layer 11	'relu7'	ReLU	ReLU
Layer 11	'drop7'	Dropout	50% dropout
Layer 12	'fc8'	Fully Connected	1000 fully connected layer
Layer 12	'prob'	Softmax	softmax
Layer 12	'output'	Classification Output	Classification Output

#### 4. RESULTS AND DISCUSSION

During this study, an AI model by using a convolutional neural network with the described AlexNet architecture is built by using the Matlab libraries to form the proposed model. The dataset consists of 110 CT scans of lung cancer cases classified into three classes: normal cases, benign cases, and malignant cases. In the training process, the dataset split into 2 groups, 70% for the training phase, 30% for the testing phase. After the end of the training which done randomly, this model gives after 86 epoch of the 100 epochs of the training, an overall accuracy of 93.548%. The accuracy of the model are shown in the following figure:

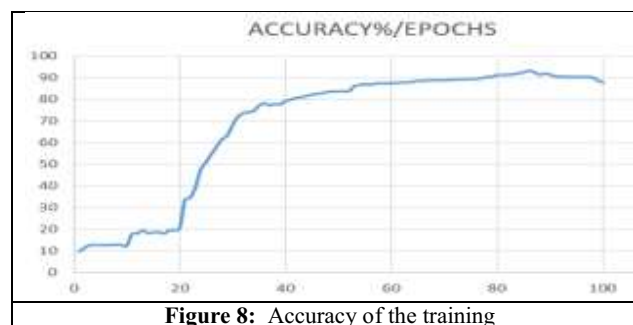


Figure 8: Accuracy of the training

The confusion matrix of the proposed model are as shown below:

Table 2- The confusion matrix

Confusion matrix		Predicted class	
		Non-malignant (positive)	Malignant (negative)
Actual class	Non-malignant	67 (TP)	3 (FN)
	Malignant	2 (FP)	38 (TN)

The performance metrics of the proposed model based on the above confusion matrix, such as **Sensitivity** (Recall) that describes the rate of true positives which accurately classified by the test(38). **Specificity** is the rate of true negatives that are perfectly classified by the test(38). **Precision** or the positive predictive value that indicates to

the portion of related cases among the total cases and F score that Represents a combination between Precision and Recall(39). All of these rates are estimated for the whole classes in the table below:

**Table 3: Performance metrics of the proposed model**

Performance metrics	Sensitivity	Specificity	Precision	F1 Score
values	95.714%	95%	97.1015%	96.403%

## 5. CONCLUSION AND FUTURE SCOPES.

This proposed study tries to defeat the problems faced in the early detection of lung cancer nodules before it gets worst. For this purpose, this study develops an effective computer-aided diagnosis scheme for early detecting of this lethal cancer. Chest tomography scans have been employed here as data input to the proposed model. This study's goal was to improve a CNN deep learning model able to detecting and classifying lung cancer nodules successfully. The obtained model gives high accuracy reaches 93.548% while applying on the dataset collected, also gives precision up to 97.1015%, sensitivity up to 95.714% and a specificity reaches to 95% approximately.

In the future, this study can be improved by includes regularly enhancing the accuracy of the model by training it on bigger and more extensive datasets. Besides, various machine learning models can be combined to compare

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