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# Use of deep learning in nano image processing through the CNN model

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**Abstract.** Deep learning is another field of artificial intelligence (AI) utilized for computer aided diagnosis (CAD) and image processing in scientific research. Considering numerous mechanical repetitive tasks, reading image slices need time and improper with geographical limits, so the counting of image information is hard due to its strong subjectivity that raise the error ratio in misdiagnosis. Regarding the highest mortality rate of Lung cancer, there is a need for biopsy for determining its class for additional treatment. Deep learning has recently given strong tools in diagnose of lung cancer and making therapeutic regimen. However, identifying the pathological lung cancer's class by CT images in beginning phase because of the absence of powerful AI models and public training data set is difficult. Convolutional Neural Network (CNN) was proposed with its essential function in recognizing the pathological CT images. 472 patients subjected to staging FDG-PET/CT were selected in 2 months prior to surgery or biopsy. CNN was developed and showed the accuracy of 87%, 69%, and 69% in training, validation, and test sets, respectively, for T1-T2 and T3-T4 lung cancer classification. Subsequently, CNN (or deep learning) could improve the CT images' data set, indicating that the application of classifiers is adequate to accomplish better exactness in distinguishing pathological CT images that performs better than few deep learning models, such as ResNet-34, Alex Net, and Dense Net with or without Soft max weights.
**Keywords:** convolutional neural network; CT image; deep learning; image processing; lung cancer

## 1. Introduction

Deep learning (DL) needs longer time and an enormous dataset to train various weights and many parameters of deep network that bring accurateness in knowledge representation. At first, the data-augmentation method as a mean to enlarge the datasets, applies the image transformation to avoiding the overfitting. Later, Graphical Processing Unit (GPU) permitted for having computing resources to a deep network train. Adding that testing and training of dataset is fundamental. AI is used to simulate some human intelligent behaviors and thinking procedures as reasoning, learning, planning and thinking. DL (subset of AI) is a multi-layer neural network (NN) model adjusted among layers and later translated into more complex abstract properties to end the learning of complicate issues (LeCun *et al*. 2015). Not so much manual intervention is needed in DL, but also it has a strong automation (Robertson *et al*. 2018). DL has more discriminative data properties from data sets compared to classic machine learning (ML). Also, the extraction procedure is straight-forward and the function could be easily set (Cheng *et al*. 2016). DL has two models as CNN and deep belief networks (DBN) say capturing 2D or 3D images and sliding window image grouping on the bases of image blocks in medical image analysis by CNN. By a deeper and more precise direction, CNN performs better (Zhou *et al*. 2018, 2022, Wang *et al*. 2020a, Xu *et al*. 2020, Zhang *et al*. 2020, Hu *et al*. 2021, Liu *et al*. 2021a, d, Lv *et al*. 2021a, b).

DL can change the information of qualitative subjective images into quantitative tangible one to assist the experts for clinical decision-making. pathological images. MRI and CT are structured data, so DL could be efficiently extracted and learnt. Deep NN has shown similar accuracy in the diagnosis of cutaneous malignant melanoma about the great potential of DL in medical image processing. The in-depth assessment by NN of retinal fundus images in the field of ophthalmology demonstrated a high level of impact and accuracy with regard to diabetes retinopathy diagnosis (Gulshan *et al*. 2016).

DL is commonly used in lung cancer pathological detection and its reporting, adding that reading slices in mechanical methods takes time and is inefficient. It is hard to evaluate the picture data due to its solid subjectivity that raise the misdiagnosis ratios. These deficiency factors, e.g., histological textures, distribution of characteristics of psycho-pathological slices of the lung cancer and cell morphology have been resolved by DL's subjective or objective diagnosis of tumor. Computer aided diagnosis (CAD) under deep learning family is used in lung cancer pathological classification. As one of the most common cancers, lung cancer brings the high death ratio in the world (5-year survival rate = lower than 18%, and 5% in patients with advanced metastatic lung cancer) that requires accurate pathological diagnosis and treatment (Xiaoru and Zhang 2018).

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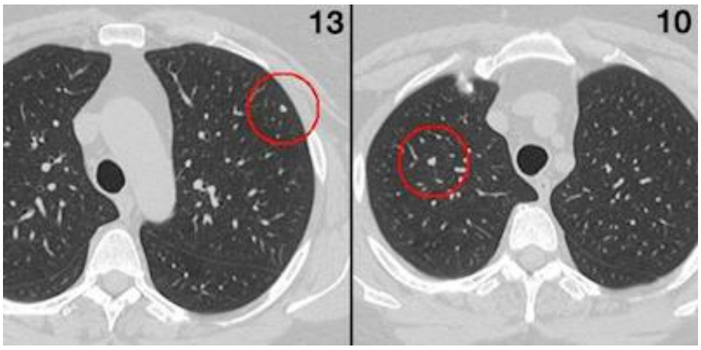



Fig. 1 Lung cancer CAD image

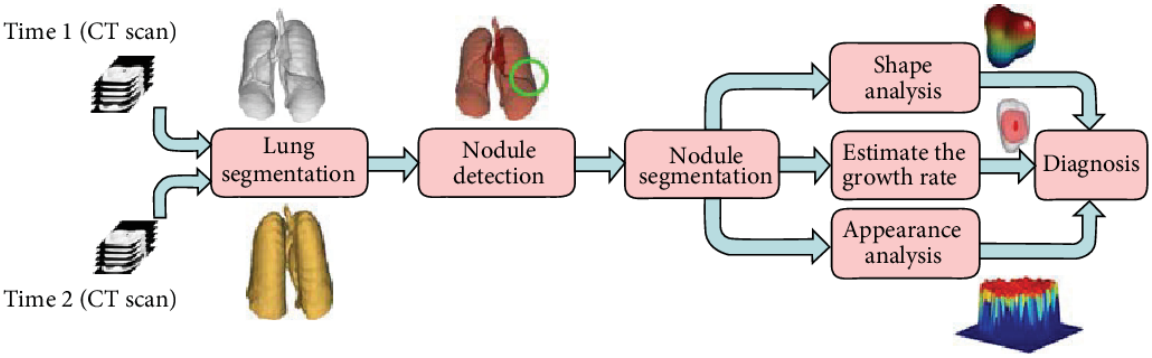



Fig. 2 Computer aided diagnosis system for lung cancer

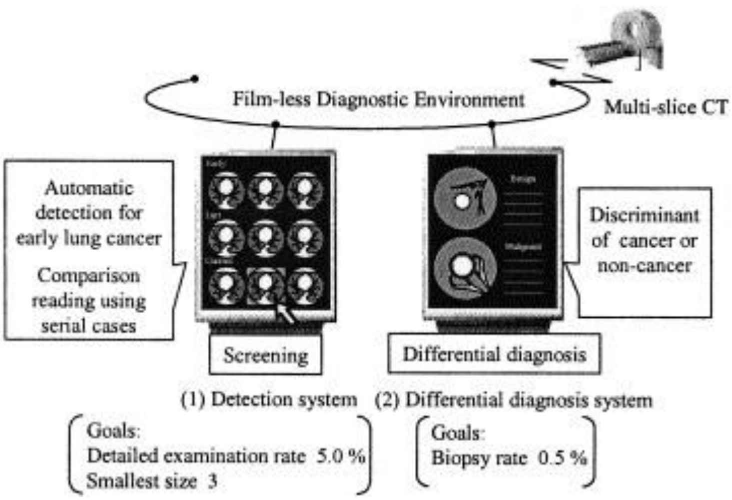
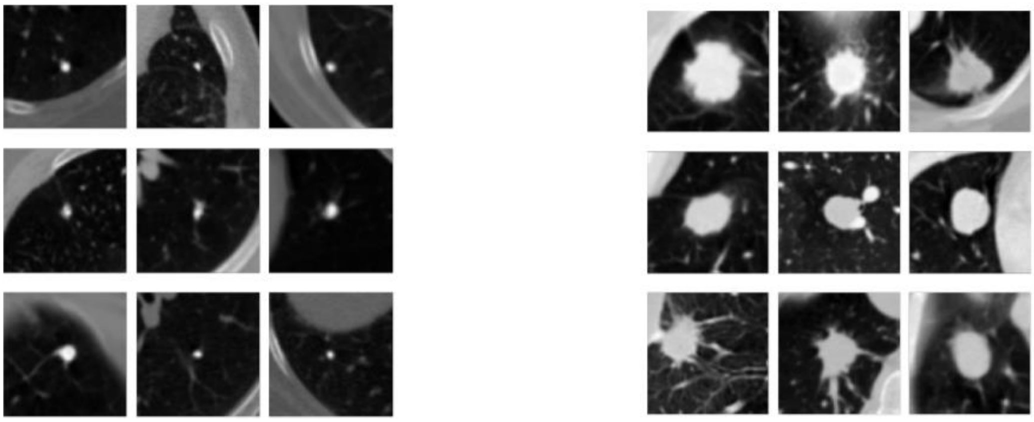



Fig. 3 A CAD system for lung cancer based on CT image

Lodwick *et al*. (1963) offered the technique of digitizing X-ray films as a practical base for the use of computers in medical data extraction. Computer aided diagnosis is the medical image processing, combination of imaging and other conceivable biochemical and physiological techniques with computer for detection of lesions or classification of benign and malignant tumors (Yanase and Triantaphyllou 2019). CAD by providing objective judgment provides an effective role to improve the doctors' efficiency, diagnosis' accuracy and lower misdiagnose. CAD incorporate the feature modeling, segmentation, classification (core of CAD system) and preprocessing, in which classification is the grouping and labeling of data mining process. Then, choosing a proper ML technique build up a classifier liable for recognizing various sorts of injuries is a vital part of CAD (Fusco *et al*. 2016).

Despite the merits of using DL in biomarkers, prognosis prediction and classification of lung cancer, there are few problems toward using DL in pathology. For example, Teramoto *et al*. (2017) have investigated the pap staining 76 cases of lung cancer including small cell carcinoma, squamous cell carcinoma and adenocarcinoma (Fazaeli *et al*. 2016, Ghazanfari *et al*. 2016, Habibi *et al*. 2016, 2018, Hosseini *et al*. 2018, Alipour *et al*. 2020, Cheshmeh *et al*. 2020,



(a) (b)

Fig. 4 Two main types of pulmonary nodules in LIDC-IDRI dataset, (a) small diameter nodules, (b) big diameter nodules

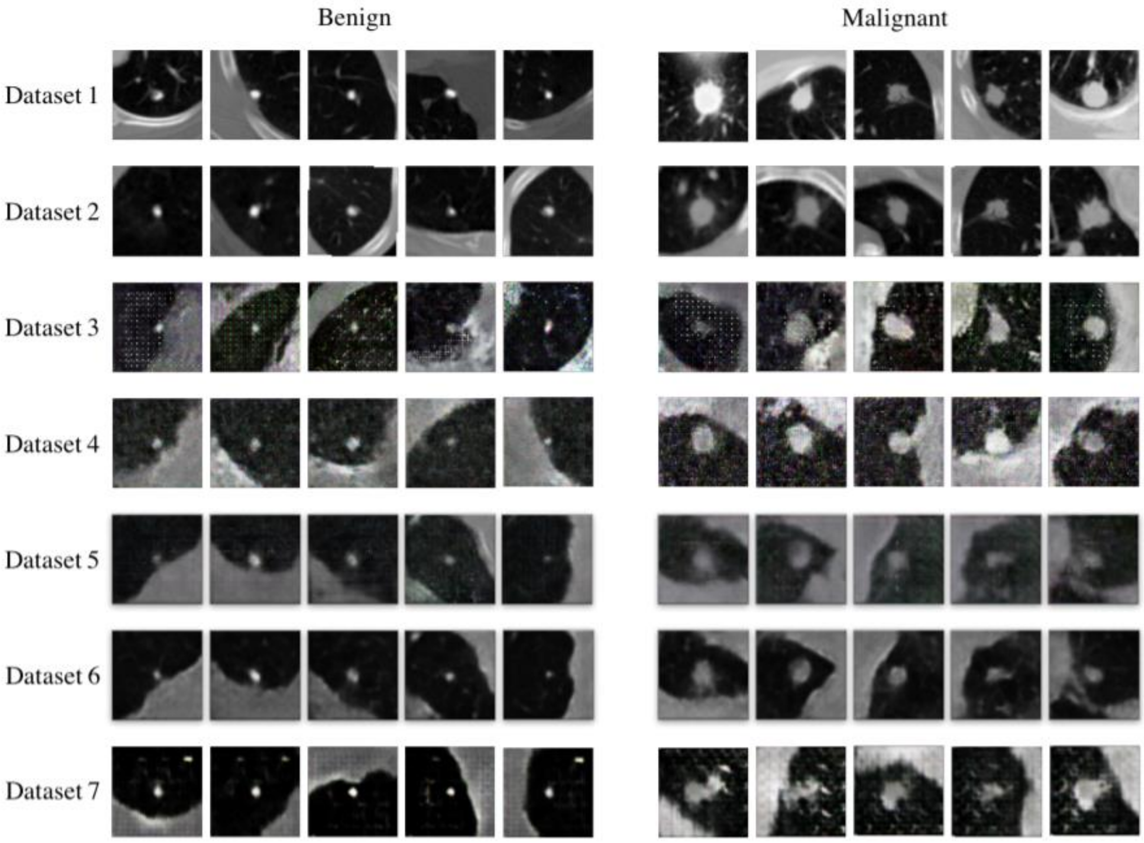



Fig. 5 The generated images. The the right block shows malignant sample and the left block shows benign samples

Ghabussi *et al*. 2020, Ghazanfari *et al*. 2020, Li *et al*. 2020a, b, Liu *et al*. 2020a, b, Moayedi *et al*. 2020c, Shariati *et al*. 2020b, Shi *et al*. 2020, Wang *et al*. 2020b). Two CNNs were trained through the main data, enhanced original. Later, the developed CNN extracted the features to detect the cancer, showing more accurate detection (71.1%). Khosravi *et al*. (2018) utilized Tensor Flow model for comparing various models to different the adenocarcinoma and squamous cell carcinoma based on two lung cancer databases as Cancer Genome Atlas (TCGA) and Stanford Tissue Microarray Database (TMAD). Many images are trained in database, but few ones are utilized to evaluate and test the model. Regarding all, Inception-V3 and Inception-V1 (pre-trained CNN) could spot the squamous cancer cell from adenocarcinoma in high resolution (100%) magnified images of local lesions. Accordingly, full slice image fluctuates between 75% and 90% in terms of classification accuracy. Early therapeutic uses are encouraged by machine and human collaboration. In both cases, a new type of pre-trained, finely tuned CNN (Inception-V1 and Inception-V3) could identify adenocarcinoma squamous cell carcinoma with magnified pictures of local lesions of 100% higher resolution. Considering full slice image, their grouping precision ranges in 75% - 90%. Hou *et al*. (2016) consolidated the sliding window classification on the bases of image blocks by classic DL to input test images, training many image data from histopathological H&E staining images of TCGA, improving 13 decision fusion models, automatic analyzing of the model, classified based on the morphological features of images, mixed lung adenocarcinoma or lung adenocarcinoma and output lung squamous cell carcinoma. The results showed more accuracy of the developed model of EM-Fine tune-CNN-SVM than CNN itself.

CAD as a new system in medical imaging has improved the quality of images from scanners through reducing error and enabling more effective interpretation of images. Therefore, CAD has worked on cardiology, pathology and radiology e.g. in radiology as colonic polyps on CT colonography, detection of masses and micro calcifications in lung nodules, mammography on CT scans and X-rays (Deng *et al*. 2009), in digital pathology as detection of cells, nuclei and diseases (cervical, prostate and breast cancers) (Szegedy *et al*. 2015) and in cardiology as angiography and echocardiography (Krizhevsky *et al*. 2012, Simonyan and Zisserman 2014, Russakovsky *et al*. 2015). There are few impediments to understanding the maximum capacity of CAD, such as its developing takes time and effort say the complex analysis of cases with proven pathology because the best proof comprises the histopathologic analysis and surgical excision. For instance, regarding the radiology images, accurate abnormality needs to be delineated by an expert that takes time and cost, then the most accurate diagnosis of abnormality comes from few experts on the same diagnosis. Consequently, the best performance of CAD is performed while analyzing tens or hundreds of proven cases, large datasets (Ordonez *et al*. 2013). Data collection has limited the performance of CAD while mostly focusing on the major fields like lung nodule diagnosis, however, clinicians have to analyze many images and interpret medical images. In a chest CT scan analysis, dozens of structures need to be analyzed while knowing many potential abnormalities as normal variants and lesions (Babenko *et al*. 2014), adding that many of these imaging problems have been ignored or under investigation. CAD also take more time, while in recent years, developing mathematical models specifically tailored to a specified shortcoming have been applied.

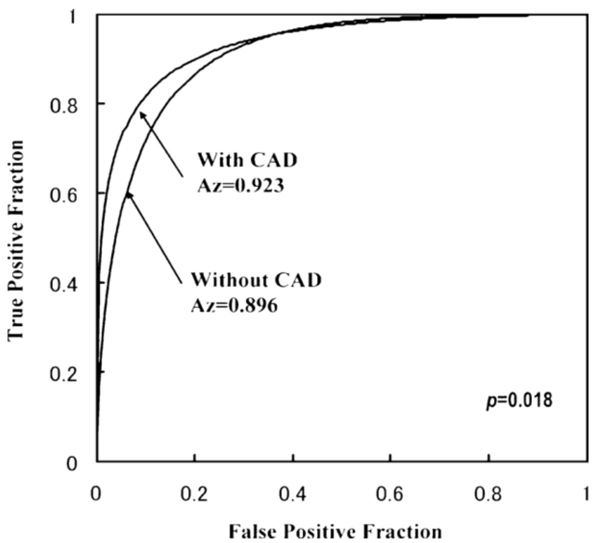


Fig. 6 Detecting lung cancer with and without CAD system

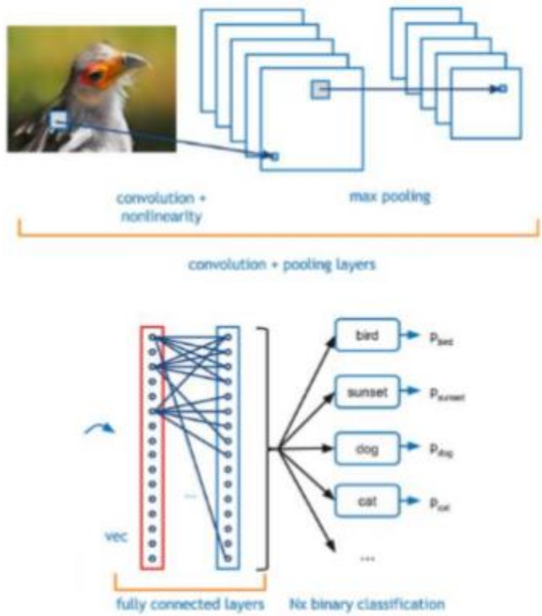


Fig. 7 Architecture of CNN

## 2. Experiment

Deep neural network (DNN) is applied as feature extractors or classifiers to determine different issues in microscopy image analyzing as segmentation, classification and target detection. In a pixel-sensitive classification, the DNN assigns a hard or soft marker to the whole image in the image classification. The last layers of CNN are normally selected as a multi- way of max function adjusted to few target classes. While using a feature extractor, a network creates a changed presentation of input image used to subsequent data analyzing as target classification or features election. Usually, the representation prior to CNN last layer is extracted in supervised learning, however, the representation from middle layers or lower layers are proper to define the object. Pre-train and fine-tune to NN is the best way to do with contingent data in clinical imaging.

## 3. Convolutional neural network (CNN)

The application of local spatial coherence in input images is one the CNN benefits, allowing them to have less weights while sharing some parameters, which is benefit in terms of complexity and memory. The layers of CNN are 1) Convolution Layer, in which a matrix (kernel) is passed over the input matrix for making a feature map for the next layer, later followed by a numerical activity as convolution

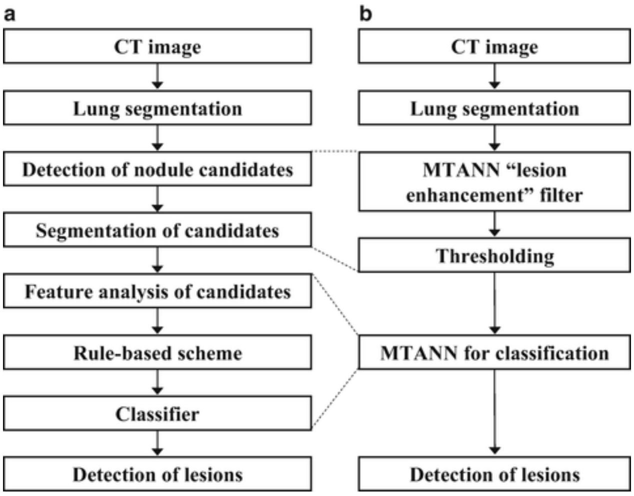



Fig. 8 flowchart of lung cancer

by sliding the Kernel matrix on the input matrix. At each location, the multiplication of an element wise matrix is done while summing the outcome onto the feature map (Moayedi *et al*. 2020a, b, Oyarhossein *et al*. 2020, Shariati *et al*. 2020a, Zhou *et al*. 2020, Dai *et al*. 2021b, Guo *et al*. 2021a, b, Huang *et al*. 2021a, Huo *et al*. 2021, Liu *et al*. 2021c, Peng *et al*. 2021, Shao *et al*. 2021, Zhang *et al*. 2021a, b, c, d).

Convolution is a specific sort of linear activity used in statistics, image processing and physics. CNN is used on more than one axis. In case of a 2-Dimensional kernel filter *(K)* and 2Dimensional image input *(i)*, the complicated image is:

$$S(i,j) = \sum_{m}\sum_{n} I\,(m,n)k(i-m,j-n)$$

b. Non-linear activation functions (ReLU) are a non-linear input signal modification in which a node arrives after the convolutionary layer and the activation function. The rectification linear unit activation function (ReLU) is a piece by piece that outputs the input when it is positive, and when the output is zero.

c. Pooling Layer, in which the problems of the feature map output of convolutional layer is that it records the exact location of features in input, meaning that image is totally led to a various feature map during rotation, cropping or other minor alternation to input. To overcome this problem, down sampling of convolutional layers is offered by using a pooling layer after nonlinearity layer, which causing the representation to be around invariant to small translations of input. Invariance to translation implies that in case of translating the input by a small quantity, the values of most pooled outputs is not changed.

d. Fully connected layer, with the last pooling layer output performed as an input in the fully connected layer, meaning that each node in first layer is connected to any node in the second layer, adding that there are one or two layers.

The strong restriction of forcing each neural interaction to use the same local propagation in all spatial translations and improving the proportion between the number of device's freedom level is presented at CNN image mapping. As a crucial issue in image processing, the high dimensionality of input data results the ill-posed defects. CNNs somehow shows the biological vision systems (Fasel 2002) while taking raw data with no need to a feature extraction stage initial or separate pre-processing, adding that in a CNN, classification and feature extraction occur normally inside a solitary framework.

## 4. CNN map

CNNs maps between temporally and spatially distributed arrays in arbitrary dimensions that seems proper to use in video, images or time series.

CNNs are divided as local connectivity, translation invariance and an optional progressive decrement in spatial resolution, which make CNN act as an interconnected filter system. Profitable comparisons might be produced among other filtering frameworks, because the neural weights of a CNN work as the system taps of wavelet filters or finite impulse response (FIR) (Dai *et al*. 2021a, Ebrahimi *et al*. 2021, Hashemi *et al*. 2021, Hou *et al*. 2021, Huang *et al*. 2021b, c, Jiao *et al*. 2021, Liu *et al*. 2021b, e, Ma *et al*. 2021, Moradi *et al*. 2021, Najaafi *et al*. 2021, Shariati *et al*. 2021, Wu and Habibi 2021, Xu *et al*. 2021, Zhao *et al*. 2021, Yu *et al*. 2022). Then, a developed CNN might be considered of trainable filter system, custom produced for a specific function mapping usage. At first, one single hidden layer and one-dimensional input are explained. Multiple layers and multiple dimensions might be involved in the extensions with possible activity of down-sampling. Acquiring the formula to change the weight and bias factors of one CNN providing a training set of input-output pairs $\xi^{\mu}_{k,r}, \zeta^{\mu}_{i,p}$. In a CNN, though they share the same weight and bias vectors, neurons are 'replicated' regarded to spatial translation. In CNN, translated neurons $h^{\mu}_{j,q}$ gain only the local connections from the prior layer. When computing the net input for a given interpreted neuron, the spatially distributed weight can be indexed by means of $s, t, u.$ indexes separately. A CNN's weights are invariant to spatial translation, so the weights are $w^{t}_{j,k,}\ t = \{-T, \dots, 0, \dots, T\}$ connecting feature array $V^{u}_{j,q}$ and input array $\xi^{\mu}_{k,r}$. $2T+1$ is the size of area surrounding each translation before the network weights exist (Azimi *et al*. 2016, Ebrahimi and Shafiei 2016, Ghadiri and Shafiei 2016a, b, c, Ghadiri *et al*. 2016a, b, c, d, Shafiei *et al*. 2016a, b, c, d, e, f, g).

$$h^{\mu}_{j,q} = \sum_{k}\sum_{t} w^{t}_{j,k}\ \xi^{\mu}_{k,q+t} + b_j \tag{1}$$

$\{p,q,r\}$ = *a spatial index for each layer,*
$\mu$ = *input pattern ,* $j$ = *hidden unit*
$q$ = *net input,* $\{i,j,k\}$ = *neuron arrays in output, hidden, and input layers*

The index to $\xi^{\mu}_{k,r}$ is clamped to spatially nearby place centered at translation $q$ by setting $r = q + t.$ $b_j$ = *usual constant bias*

The neural output makes the hidden feature arrays done by transfer performance

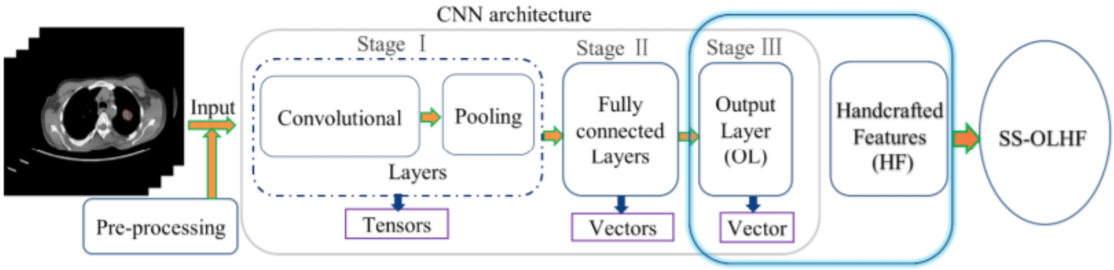



Fig. 9 CNN model

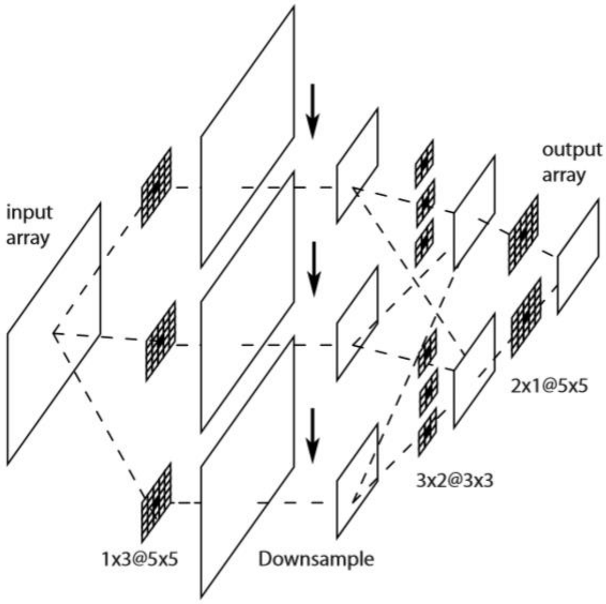



Fig. 10 Architecture of a fully interconnected CNN with multiple neurons

$$V_{j,q}^{u} = g\left(h_{j,q}^{u}\right) \tag{2}$$

In output layer, the neuron at translation $p$ in $i^{th}$ array receives net input

$$h_{i,p}^{u} = \sum_{j}\sum_{s} w_{i,j}^{s}\, V_{j,p+s}^{u} + b_i \tag{3}$$

$s = \{-S,..,0,\ldots,S\}$ and $2S+1$ is the length of filter in output layer, also the relative indexing was replaced for absolute indexing $q = p+s$. Ultimate output is

$$O_{i,p}^{u} = g\left(h_{i,p}^{u}\right) = g\Big(\sum_{j}\sum_{s} w_{i,j}^{s}\; V_{j,p+s}^{u} + b_i \tag{4}$$

### 4.1 Delta rule for CNNs

Though CNNs applied the same weight update rule as normal NN, there is a need to care more, especially with differential indexing of feature maps and spatial translation. Regarding the normal ANNs, the CNN's cost function is:

$$E = \frac{1}{2}\sum_{\mu,i,p}[\,\zeta_{i,p}^{u} - O_{i,p}^{u}]^{\,2} \tag{5}$$

Derivative of the error was gained regarded the $s^{th}$ weight of filter joining the $i^{th}$ output array to $j^{th}$ feature array.

$$\frac{\partial E}{\partial w_{i,j}^{s}} = -\sum_{\mu,p}[\,\zeta_{i,p}^{u} - g(h_{i,p}^{u})]\; g'(h_{i,p}^{u})\; V_{j,p+s}^{u} \tag{6}$$

Used in combination with the familiar gradient descent weight update rule

$$\Delta w_{i,j}^{s} = \eta \sum_{\mu,p} \delta_{i,p}^{u}\; V_{j,p+s}^{u} \tag{7}$$

where

$$\delta_{i,p}^{u} = [\,\zeta_{i,p}^{u} - g(h_{i,p}^{u})]\; g'(h_{i,p}^{u}) \tag{8}$$

For finding the weight alteration of input to hidden connections $w_{j,k}^{s}$, delta rule is used with a indices' change (Ebrahimi and Shafiei 2017, Ebrahimi *et al*. 2017, Ehyaei *et al*. 2017, Ghadiri *et al*. 2017a, b, c, d, e, Mirjavadi *et al*. 2017a, b, c, d, Shafiei and Kazemi 2017a, b, Shafiei *et al*. 2017a, b, c, d, 2019, 2020, Shivanian *et al*. 2017, Azimi *et al*. 2018, Shafiei and She 2018)

$$\Delta w_{j,k}^{s} = \eta \sum_{\mu,p} \delta_{j,q}^{u}\;\; \xi_{k,q+t}^{u} \tag{9}$$

$$\delta_{j,q}^{u} = \sum_{s} g'(h_{j,q}^{u}) \sum_{i} \delta_{i,q-s}^{u} \; w_{i,j}^{s} \tag{10}$$

### 4.2 Down-sampling

The past equations are changed for computing the output of network, adding that the two layers incorporate spatial down-sampling that was already done by another 'averaging' layer with fixed neural weights (LeCun *et al*. 1989), which is explained below by raising the shift indexes by a factor of two, then integrating of down-sampling and adaptive functions. The averaging layer in Le Cun *et al*. (1989) technique might be proper by a 'double shift' layer with a filter size of 2, and allowing to adapt the previously fixed averaging weights

$$h_{j,q}^{u} = \sum_{k} \sum_{t} w_{j,k}^{t} \; \xi_{k,2q+t}^{u} \; + \; b_i \tag{11}$$

$$h_{i,p}^{u} = \sum_{j} \sum_{s} w_{i,j}^{s} \; \xi_{j,2p+s}^{u} \; + \; b_i \tag{12}$$

The output of the network is then

$$O_{i,p}^{u} = g(\sum_{j} \sum_{s} w_{i,j}^{s} \; g(h_{j,2p+s}^{u}) + \; b_i) \tag{13}$$

$$O_{i,q}^{u} = g(\sum_{j} \sum_{s} w_{i,j}^{s} \; g(\sum_{k} \; \sum_{t} w_{j,k}^{t} \, \xi_{k,4p+2s+t}^{u} + \; b_i) + b_i \tag{14}$$

Regarding a normal CNN with $N$ layers and filter sizes ($F_n$), the local region(s) of input contributing to output is given as Eqs. (15) and (16)

$$R_{n+1} = R_n + F_n - 1 \; if \text{ non} - \text{down} - \text{sampling} \tag{15}$$

$$R_{n+1} = 2(R_n + F_n) - 3 \;\; if \text{ non} - \text{down} - \text{sampling} \tag{16}$$

Regarding the fixed filter sizes $F_n$, obviously the input 'window' of CNN might be developed quickly because of the increment of down-sampling layers. Many wavelet changes use a comparable nested series of down-sampling tasks, accomplishing important computational savings. The weight update rules are similar to (Lawrence *et al*. 1997) and (Säckinger *et al*. 1992) if the shift indices $p$ and $q$ was raised by a multiple of two For down-sampling layers (Ebrahimi and Shafiei 2017, Ebrahimi *et al*. 2017, Ehyaei *et al*. 2017, Ghadiri *et al*. 2017a, b, c, d, e, Mirjavadi *et al*. 2017a, b, c, d, Shafiei and Kazemi 2017a, b, Shafiei *et al*. 2017a, b, c, d, 2019, 2020, Shivanian *et al*. 2017, Azimi *et al*. 2018, Shafiei and She 2018).

## 5. Conclusions

To sum up, lung cancer pathology based on DL, CAD and scientific analysis showed the good function and high potential, adding that there are many to be still investigated in DL while the processing accuracy and few difficult performances need to be accomplished. Both scientific studies and clinical researches are difficult works that need more requirements. Right now, it is impossible to use solely and directly of DL in medical practices and clinical works. In this research, CNN was used to classify the lung cancer lesions images. 472 patients were selected, divided to validation, training and test groups subjected to staging FDG-PET/CT in 2 months prior to surgery or biopsy. Based on the result, CNNs showed a feasible and promising function in evaluating the T-parameter in lung cancer, also it could maintain few minutes from the baseline PET/CT possibility of a patient (T1-T2 or T3-T4). Comparing to radiomics, CNNs have the benefits of reducing the feature calculation, tumor segmentation and selection that could be highly critical tasks in small lesions. It is hoped that DL based lung carcinoma pathology CAD could be consistently developed and accurately and deeply participate in all the features of lung carcinoma pathology to assist the experts for processing the massive data.

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