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Lung Cancer classification using an ensemble of CNNs Method in CT Scan Images

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Abstract

About five million people lose their lives every year to lung cancer, making it one of the leading causes of mortality worldwide. In the last few years, a lot of methods of detection of lung cancer were improved however these could not efficiently diagnose cancer. In this paper, a convolutional neural network (CNN) of robust deep learning is developed. CNN precision raises the deeper that is, however, it causes over-fitting or vanishing gradient problems simultaneously. To solve the issue, the CNN used resort to parallel CNN. It used Pictures the LIDC-IDRI consortium image collection has thoracic CT images that have been annotated for lung cancer diagnosis and screening purposes. The presented model includes result models of CNN which are integrated via ensemble methods and it compare with every model. Results of the simulation illustrate that the presented method's accuracy has developed by 2.18 percent in comparison with the method of the main paper

Keywords: Deep learning, CNN, Lung cancer

1. Introduction

Cancer refers to cells proliferation and abnormal growth in body. While the cancer improves, cells go on to uncontrollably grow and share with no death. Indeed, cells have lost their normal growth and specificity of site [1]. In Lung cancer detection term, received image require to be pre-processed and detect whether suspected areas are tumor/not. While cells in lung tissues are raised in the uncontrolled way that leads in generating disease of lung cancer [2]. With no treatment, the growth could move to the other close tissues that known as metastasis. Most of the cancers of lung obtain from epithelial cells, which are a kind of cell which lines body surfaces. Lung cancer diagnosis is too essential, due to that early disease diagnosis could cause in better treatment. That is too hard task for a doctor, since a lot of factors exist influencing decision on cancer kinds' diagnosis [2].

Deep learning contains the network training for mimicking humans' abilities to perform tasks like object detection, image identification, class prediction, speech recognition. This is the exceptional learning based on representation by architecture generating inherent features from sequenced hidden neurons layers. That is termed "deep" obtained from multiple hidden layers of Artificial Neural Network structure [3]. CNN is the trainable multi-layer network structure included hybrid single-layer CNNs [4]. Such models of deep learning have obtained great image classification challenges performance in various domains, such as medical image analysis, specifically on histopathology images [5].

However, models of CNN have obtained appropriate outcomes in grouping the images, large opinion behind CNNs is that the local image understanding is good, yet there is a number of issues like classes' diversity and similarity between the classes. This problem solution is applying function of loss. In addition, data shortage in wide neural networks might cause in overfitting in such networks [6]. Overfitting happens while the model learns to memorize samples of training that cannot generalize well for sets of test and validation.

The innate medical images features, such as the high dissimilarity of intraclass and low intraclass variability, and weak network focus on them, because of cross-entropy (CE) loss use, cause in decreasing images classification accuracy. In addition, as the last convolutional layer in CNN has highly class-specific information, providing equal importance to whole channels leads in extracting less discriminative features compared with adaptively weighting every channels. The fact that data labeling and creating ground truth on wide set of data is expensive is the other concern point in this case [7]. CNN precision raises deeper it is, however it leads to the problem of over-fitting/vanishing gradient simultaneously. For solving this problem, we resort to the parallel CNN. Presented model includes model of CNN which leads in models which are integrated via ensemble techniques and compare that with every model.

This paper motivation was launching the ensemble model which applies majority voting approach to screen chest Lung cancer images of CT. In the pre-trained model of CNN, quality and speed of learning are assigned by hyperparameters of algorithm which are set before process of learning starts. In subsequent training, various pre-trained models of CNN might need various hyperparameters of algorithm (such as learning rate, mini-batch size, and optimizer) for improving the accuracy of classification. Present paper applied uniform experimental design (UED) for creating algorithm hyperparameters integration for the pre-trained model of CNN. Tests illustrated that ensemble model of Lung cancer- CNN had superior accuracy of classification in comparison with the single model and great accuracy in grouping CT images of chest autonomous pulmonary nodules classification, many deep learning as Lung cancer positive/negative. For algorithms have been developed due to their high performance and small end-to-end footprints. In other words, researchers adapted pre-existing CNNs that have shown to be particularly adept at representing and analyzing natural images, and then used those CNNs in practical contexts through transfer learning. AlexNet, LeNet-5, ResNet, GoogLeNet, and VGG are some of the most widely used networks. However, many publications created their own CNNs. Though occasionally the lone learner exhibits unsatisfactory performance because to restricted hypothesis space issues, incorrect hypothesis space selection, or a fall into a local minimum. Some frameworks using ensemble CNN models have been executed to improve the precision of clinical decision-support systems.

The second section is a review of the literature. In Section 3, the proposed procedure is described. Section 4 discusses the results of the experiments, while Section 5 presents the paper's conclusions.

2- Literature review

In this section the researches into deep learning classification and diagnosis systems. Lakshmanaprabu & Mohanty in 2019 [8], An ODNN and a linear discriminant analysis were used to analyses a CT scan of the lungs. Classifying lung nodules as benign or malignant requires deep features collected from CT lung images and feature dimensionality reduced via LDR. Optimized using the Modified Gravitational Search Algorithm (MGSA), CT images are fed into ODNN for lung cancer categorization.

Pham & Futakuchi in 2019 [9], A novel two-step deep learning technique was developed to better deal with the false-positive prediction problem without sacrificing accurate cancer detection. We collected 349 whole-slide pictures of lymph nodes from patients with lung cancer for training the algorithm, evaluating the algorithm, and validating the algorithm. In the first step, noncancerous regions (lymphoid follicles) that are frequently misclassified as cancerous were eliminated using a deep learning system. In the second phase, advancements were made to the deep learning classifier used to identify cancerous cells.

Suresh & Mohan in 2022 [10], Using a Deep Convolutional Neural Network (DCNN) trained from inception, a method is presented for automatically determining the stage of malignancy of pulmonary lung nodules. In this research, we utilized 1018 images from the Lung Image Database Consortium and the Infectious Disease Research Institute (LIDC-IDRI) public repository. Four radiologists segment lung computed tomography (CT) images containing potential nodules into a 52-by-52-pixel nodule region of interest (NROI) rectangle annotated with ground truth (GT) values. User-learned retrieval and evaluation strategies for significant NROI features, such as nodules with varying structures. DCNN are taught using NROI cases, which are classified according to benign or malignant tumor patterns. In order to prevent overfitting, dropouts and data augmentation are employed.

Asuntha, & Srinivasan in 2020 [11], Malignant pulmonary nodules can be found with the help of cutting-edge Deep Learning algorithms. Some of the state-of-the-art feature extraction methods used here include the Scale Invariant Feature Transform (SIFT), the Histogram of oriented Gradients (HoG), the Zernike Moment, the wavelet transform-based features, and the Local Binary Pattern (LBP). The optimal feature is chosen using the Fuzzy Particle Swarm Optimization (FPSO) method after geometric, textural, intensity, and volumetric data have been extracted. At last, Deep Learning is used to classify these characteristics. The cutting-edge FPSOCNN strategy simplifies the computation needed for CNNs. The second dataset is obtained in near real-time from Arthi Scan Hospital and is the topic of further analysis. The results of the tests prove that the unique FPSOCNN is better than the existing alternatives.

Garg & Salehi in 2022 [12], Using chest CT scans to diagnose COVID-19 cases using an ensemble deep convolutional neural network (CNN), as described by the authors. CT scan images are used to train, validate, and build three deep CNN models with variable hyperparameters. Rules of ensemble hard voting are utilized to classify Non-COVID and COVID situations, integrating the prediction values from these models to increase prediction accuracy and decrease the overall false prediction rate.

Heidari & Jafari in 2022 [13], The Contrast Limited Histogram Equalization (CLAHE) preprocessing stage was implemented to enhance the quality of CT images. The authors then fine-tuned a novel CNN model that had previously extracted 100 salient characteristics from a total of 2482 CT scan images. Support Vector Machine [SVM], Random Forest [RF], Gaussian Naive Bayes [GNB], Decision Tree [DT], and Logistic Regression [LR] utilized the retrieved characteristics.

Zhou & Huang in 2023 [14], The authors refine the one-step preprocessing required to downsize CT chest images to a stable size (256 by 256 pixels), therefore maintaining the original aspect ratio and minimizing data loss. Using an ensemble of approaches and a lightweight, pre-trained Convolutional Neural Network

(CNN) model called EfficientNet-B3, they present a deep learning (DL) approach to classifying CT chest images. The presented method, which we call EfficientNet-B3-GAP-Ensemble, is an ensemble of EfficientNet-B3 variants with improved accuracy and performance. Using a combination of hybrid training runs and epochs, they form an ensemble. On SARS-CoV-2-CT and COVID19-CT, two standard benchmark datasets, they conduct experiments with EfficientNet-B3-GAP-Ensemble.

Ingle & Kim in 2022 [15], The new strategy based on ensemble for more appropriate disease detection of COVID-19 by applying images of CT scan is presented. This study exploits learning of transfer by applying pre-trained deep networks (like ResNet, VGG, Xception) evolved by genetic algorithm, integrated in ensemble architecture for lung lobes clustered images classification. This paper is validated on novel set of data achieved as present ones' combination. Experimental assessment outcomes illustrate that classifier of ensemble guarantees the efficient performance, showing better capabilities of generalization.

Ascencio & Reyes in 2022 [16], The authors studied 4,171 CT pictures from 210 patients taken from the publicly accessible multiclass dataset of CT scans. We employed a pool of convolutional neural networks (CNNs) that had been pre-trained on the ImageNet dataset to extract features from CT scans; these CNNs selected their feature subset using the Information Gain filter. To evaluate the accuracy of each CNN's classification, a set of k Nearest Neighbors classifiers was trained using 10-fold cross validation on the collected feature vectors. Images were ultimately categorized as "NO COVID-19" or "COVID-19" based on a majority vote.

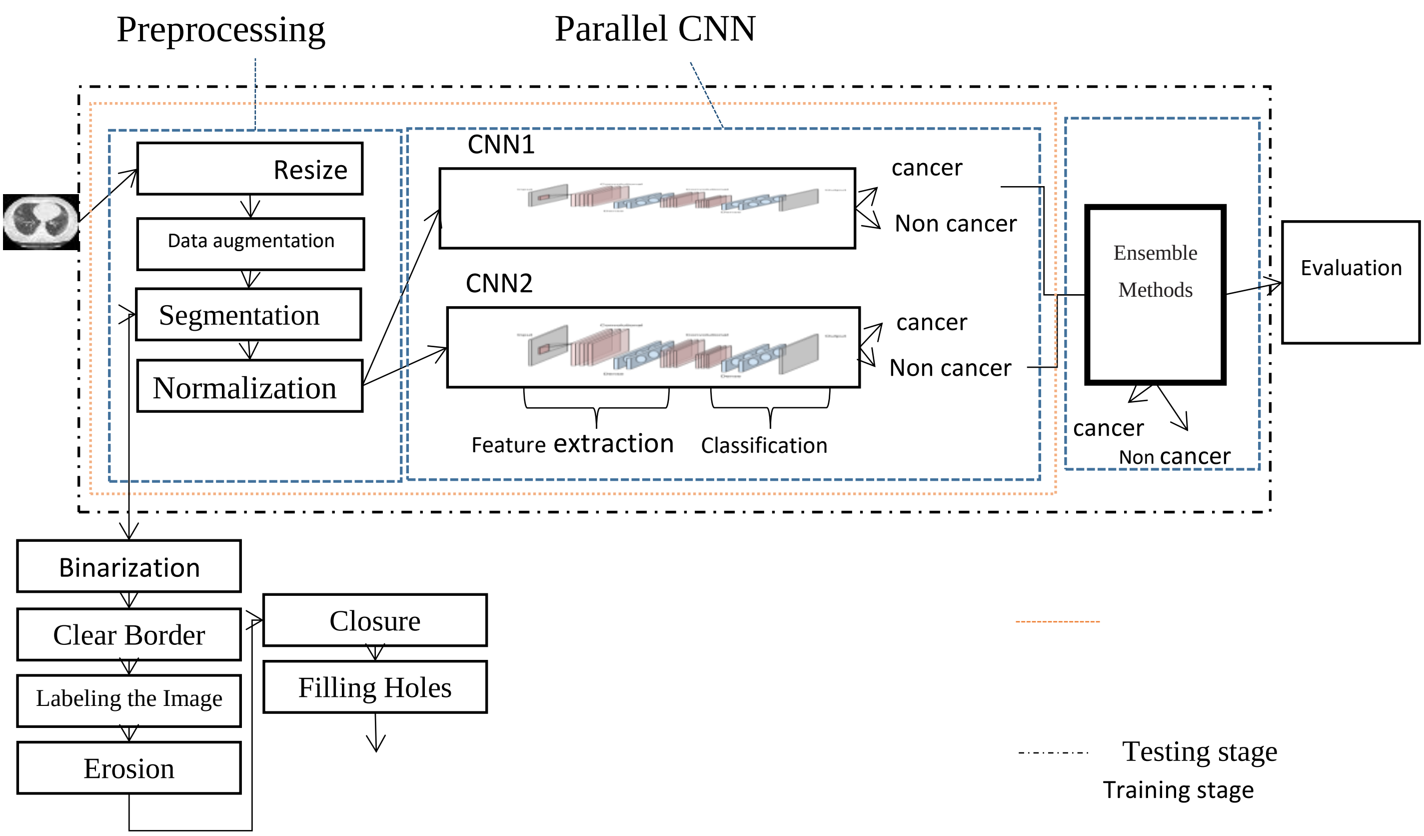
Macas & Fuertes in 2022 [17], The new method of ensemble intrusion detection is presented for defensing tacks of network in contrast to train ECN, specifically IP Scan, Man in the Middle (MITM), Denial of Service (DoS), and Port Scan. Thirty-four features of various contents of protocol are extracted from raw data created from our ECN testbed for forming the particular set of data. The method of data imaging and method of temporal sequence building are designed for optimizing set of data. Six base classifiers are created given some normal CNNs and RNNs: GRU, SimpleRNN, LeNet-5, VGGNet, AlexNet, and LSTM. The dynamic voting method of weight matrix is presented for combining whole basic classifiers.

Waleed & Azar in 2022 [18], Aimed for methods based on leverage deep learning to automated COVID-19 classification from viral and normal pneumonia on CXRs, as well as COVID-19 biomarkers indicative areas' identification. Basically, the writers segmented and preprocessed areas of lung by applying method of DeepLabV3+, subsequently cropped areas of lung. The cropped areas of lung were applied as the inputs to some deep CNNs for COVID-19 prediction. Set of data was highly unbalanced; majority of vast were usual images, by small COVID-19 and pneumonia images number.

3. Proposed method

The proposed method included three stages the are preprocessing, architecture of CNN and Ensemble learning. The first block begins by Resize that changes images of The CT input image partitioned into blocks with size 224*224. Like augmentation of data, various types exist like zooming, rotation, transformation, flipping, shifting which were chosen in order to be used to the basic set of data and raising presented performance, after that segmentation of lung is applied for separating area of lung from image, for removing distinguishing challenge among boundaries of lung and injury, normalizing to standardize images with sharing that by 255, it is the block of preprocessing. Second block includes 3 networks of CNN, 2 for learning of transfer and 1 by the presented architecture. The Third block every network is trained applying set of data gathered from various sources and the performance of it is assessed and compared to 3 networks' results which are gathered and trained on similar set of data with classifier combination/Ensemble methods to improve accuracy of classification with collecting multiple classifiers predictions.

Fig. 1 illustrates diagram of block that shows presented framework method.



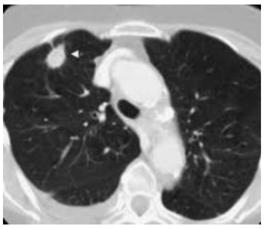


Figure 1- the proposed system

3.1 preprocessing

As base of data was gathered from various sources, that is identified to that the sizes of it might differ in width, length/both, therefore that is essential for making the resize in 224 * 224.

Data augmentation usage is to raise training images number using random transformations to images. For instance, we could crop images/randomly rotate / horizontally flip them.

An image is shared in groups/ areas which are compatible by various organisms. multi segmentation methods exist:

- Segmentation based on Region
- Segmentation of Edge Detection
- Clustering-based Image segmentation

3-1-1- Region Based Image Segmentation

Segmentation based on Region is relatively simple and more immune to noise in comparison with method of edge detection. In methods based on region, partition the image in areas which are the same based on the predefined criteria set. Segmentation methods based on Region are shared in 3 basic sections, such as region merging, growing, splitting. Region growing is the sequential method based on region in neighboring pixels are scanned and added in wider areas given the predefined seed pixels, stop conditions, growing criteria. Region splitting is for sharing an image in disjoint areas' set that are coherent in themselves. The process of area merging is applied after every split that compares adjacent areas and merges them when essential.

3-1-2- Edge Detection segmentation

In process of image segmentation, detection of Edge is main stage applied for finding objects' boundaries in images. Detection of edge is achieved by recognizing quick brightness changes/discontinuities. That usually includes discontinuity arranging points in curved line edges/parts. Detection of edge for methods of image segmentation are methods of Gradient and Gray histogram. Some operators are applied by method of edge detection, like Prewitt, Classical edge detectors, Roberts Laplacian of Guassian(LoG), zero crossing, color edge detectors, Canny Edge detector, Sobel, and so on.

3-1-3- Image segmentation based on clustering

Clustering is the strong method in segmentation of image. Some methods of clustering exist like adaptive k means, k means, improved fuzzy c mean algorithm (IFCM), fuzzy c means (FCM). clustering algorithm of K-Means is the unsupervised algorithm applied for segmenting undesired region from background. That clusters/ shares provided data in K-clusters.

3-1-4- Mask R-CNN

Mask R-CNN is mentioned as a technique for detecting and segmenting objects. In addition to attracting a bounding box around the object of interest, this technique could be used to identify the object in question, label its border, and pinpoint its central features.

With the help of Faster R-CNN, Mask R-CNN is able to create an application in the field of picture segmentation. Similar to Faster R-CNN, the Mask R-CNN technique uses a region proposal network (RPN) to extract features, and it also uses RPN to cluster and constrain feature extraction boxes. RoIPool is used in faster R-CNN as a feature extraction approach, allowing for a thorough quantification of the RoI across the board. This basic RoI of the image and the extracted features are misplaced due to the process-induced loss of spatial information. Mask R-CNN has replaced Faster R-CNN as the solution to the problem. In order to mark the region of the object where the RoI alignment (RoIAlign) was successful, a mask is successively applied from a branch.

3-2- CNN architecture

We apply 3 basic layers' kinds for creating architectures of CNN: Activation Layer, Fully-Connected Convolutional Layer and Pooling Layer. Layer,

Convolutional Layer: the duty of this layer is extracting features from images of input where taken this as the most essential CNN part. Such layers have the kernels' chain by which that has to implement the convolution. The first layer extracts low level features, the highest features level are extracted and as depth raises.

Activation Layer: the CNN depends on functions of activation which are non-linear and facilitate complicated data learning and various kinds of them exist like sigmoid, ReLU, tanh.

Pooling Layer: The position of it is among architecture of CNN and convolutional layers as that decreases parameters and computations number and handles overfitting with decreasing spatial size in network.Max and Average pooling are 2 operations in this layer.

Fully-connected Layer: That is the last CNN layers, where the layer gathers last layers' weights, for example that treats results from last layers as inputs and changes them in single vector which could be applied as the input for steps below.Here, CNNs were applied for grouping layers' number and data in network is equal to 15 layers that is specified in layers Table 1.

Table 1- Layers of convolutional neural networks

#	layers
1	imageInputLayer
2	convolution2dLayer
3	batchNormalizationLayer
4	reluLayer
5	maxPooling2dLayer
6	convolution2dLayer
7	batchNormalizationLayer
8	reluLayer
9	maxPooling2dLayer
10	convolution2dLayer
11	batchNormalizationLayer
12	reluLayer
13	fullyConnectedLayer
14	softmaxLayer
15	classificationLayer

3.3 Ensemble learning

Due to that an attempt spent on training remaining networks is not wasted. Network which outperforms in dataset of validation does not have the best performance necessarily on novel dataset of test. As several models illustrate better performance in diagnosing large objects, unlike the other models, they outperform in detecting small objects.[19]Such defects exist in last strategy where model which provides the best performance is selected and the other models are neglected, Novel strategy is Ensemble methods which train hybrid networks on similar set of data and gather their predictions to obtain last outcome. Ensemble of Model is the strong path for getting the best feasible outcomes.[20]CNN performance is dependent on architecture of network, training samples' number and on design of data normalization. Although, neither a single architecture nor a pre-processing exists which promises best performance. For a reason (GoogLeNet, ShuffleNet, mentioned above, we apply 3 CNNs trained to form the ensemble MobileNetV2).

3-3-1- ShuffleNet

ShuffleNet is the CNN which is trained on more than 1 million images from database of ImageNet. network could group images in 1000 groups of object like pencil, mouse, keyboard, and a lot of animals. Therefore, network has learned rich representations of feature for large images' range. network has the size of image input of 224-by-224. Unit of ShuffleNet is the residual construction and includes structure of bottleneck. Depthwise convolution which is computationally economical is used on residual branch map of bottleneck feature. Unit of channel shuffle is applied for increasing exchange of data among various sets of input and output. In comparison with ResNeXt and ResNet, ShuffleNet benefits are less parameters and lower complexity. for lower overhead as depthwise convolution just used on map of bottleneck feature, that is suited for low-power devices of mobile.

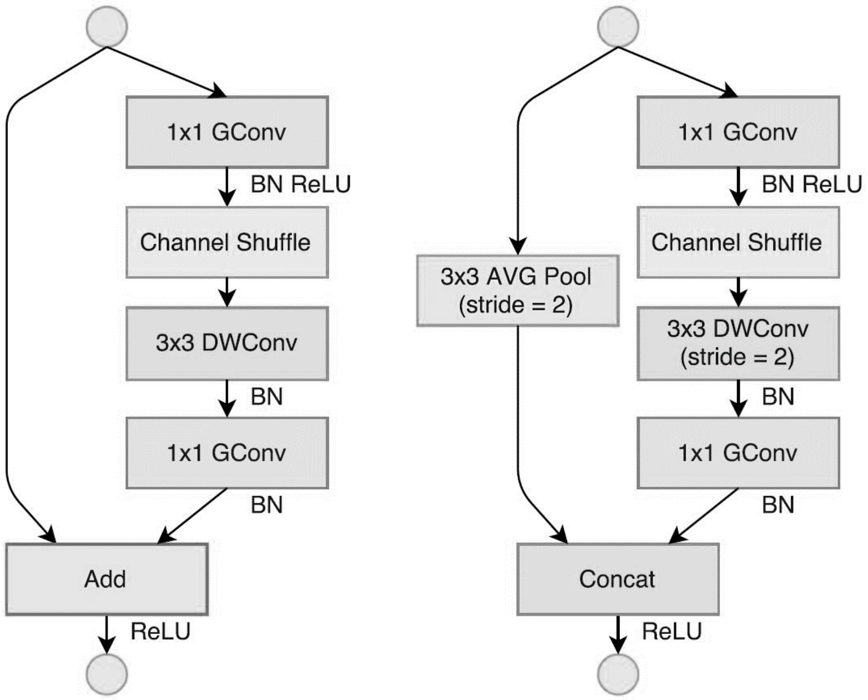


Figure 2- Two structures of the ShuffleNet unit [21]

3-3-2- MobileNetV2

MobileNetV2 is the architecture of CNN for devices of mobile presented by Sandler et al. the first version of it was designed for detection of face feature but trained and assessed on dataset of Googles inhouse. They define inverted residuals and linear bottlenecks and obtain new outcomes balancing inference time and performance for typical benchmarks such as VOC, ImageNet, COCO.

MobileNetV2 is the architecture that achieves a good balance between performance and memory usage while incurring a small mistake penalty. When minimal memory consumption is a desirable attribute in a network ensemble scenario, the quick speed of execution facilitates experimentation and parameter adjustment. Inverted residual and depthwise separable convolution, two key principles defining the MobileNetV2 architecture, will be explored further.

Other powerful models, such as ShuffleNet and MobileNets, also use depthwise separable convolution. Traditional convolution is replaced with depth-separable convolution, which requires two processes instead of one. The first step is feature map-wise convolution, in which a unique convolution is applied to each feature map. As a second step, the pointwise convolution is applied to the stacked feature maps that were generated. The kernel of the pointwise convolution is 1 1, and it is used to convolve entire feature maps all at once. Images in both the vertical and horizontal planes are processed simultaneously by the conventional layer. An image is initially processed along its width and height in the first operation of depthwise separable convolution, and then along its channel in the second operation, which is the typical layer factorization.

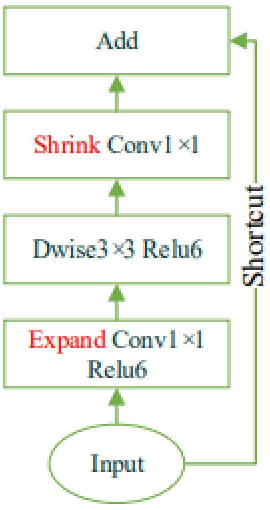


Figure 3- Structure of the MobileNetV2 [22]

3-3-3- GoogLeNet

Google's GoogLeNet (also known as Inception V1) won the ILSVRC 2014 competition. A 6.67 percent rate of error in the top five was achieved. Human performance in the task could not be judged accurately using this method. To beat the accuracy of GoogLeNets, it turned out to be quite challenging and require multiple rounds of human training. A human expert (Andrej Karpathy) was able to achieve a top-5 error rate of 5.1% (single model) and 3.6% (ensemble) after only a few days of training. The network used a CNN modelled after LeNet, but it also included a novel, ingeniously designed module. As a result, RMSprop, batch normalizing, and distortions in the images were implemented. To dramatically lower the total number of parameters, few tiny convolutions are applied to the module. Although a deep CNN architecture with 22 layers was used, the number of parameters was reduced from 60 million (AlexNet) to 4 million. GoogLeNet's architecture consists of 22 layers (27 if you count the pooling layers), each of which is composed of 9 inception modules (fig. 4).

type	patch size/ stride	output size	depth	#1×1	#3×3 reduce	#3×3	#5×5 reduce	#5×5	pool proj	params	ops
convolution	7×7/2	112×112×64	1							2.7K	34M
max pool	3×3/2	56×56×64	0								
convolution	3×3/1	56×56×192	2		64	192				112K	360M
max pool	3×3/2	28×28×192	0								
inception (3a)		28×28×256	2	64	96	128	16	32	32	159K	128M
inception (3b)		28×28×480	2	128	128	192	32	96	64	380K	304M
max pool	3×3/2	14×14×480	0								
inception (4a)		14×14×512	2	192	96	208	16	48	64	364K	73M
inception (4b)		14×14×512	2	160	112	224	24	64	64	437K	88M
inception (4c)		14×14×512	2	128	128	256	24	64	64	463K	100M
inception (4d)		14×14×528	2	112	144	288	32	64	64	580K	119M
inception (4e)		14×14×832	2	256	160	320	32	128	128	840K	170M
max pool	3×3/2	7×7×832	0								
inception (5a)		7×7×832	2	256	160	320	32	128	128	1072K	54M
inception (5b)		7×7×1024	2	384	192	384	48	128	128	1388K	71M
avg pool	7×7/1	1×1×1024	0								
dropout (40%)		1×1×1024	0								
linear		1×1×1000	1							1000K	1M
softmax		1×1×1000	0								

Figure 4- GoogLeNet incarnation of the Inception architecture [23]

3.2Evaluation

In this section, at first, we assessed model performance defined in Table 2. Presented method was written in Matlab programming language. Model output is proposed method comparison curve by present methods as described in part 4-4. As an output, Sensitivity, Specificity, Accuracy were presented by model.

3.3Dataset

Database of Chest Pictures the LIDC-IDRI consortium image collection has thoracic CT images that have been annotated for lung cancer diagnosis and screening purposes. This online database serves as a global hub for training, development, and assessment of CAD approaches for the early detection and diagnosis of lung cancer. Public-private collaboration demonstrates consortium success recognized on approach based on consensus; initiative by National Cancer Institute (NCI), enhancement by Foundation for National Institutes of Health (FNIH), and active engagement by Food and Drug Administration (FDA).

The 1018 instances in this dataset are the result of a collaborative effort between eight medical imaging businesses and seven academic institutions. The XML file associated with each patient comprises the results of a two-stage picture annotation process conducted by four seasoned thoracic radiologists. Initial CT scans were blind-read, and radiologists categorized lesions into three categories based on their size: nodule (more than or equal to 3 mm), nodule (less than or equal to 3 mm), and non-nodule (greater than or equal to 3 mm). Each radiologist then unblindedly examined the ratings given to them by a panel of three other radiologists for their interpretation of the final concept. The ultimate goal of this procedure was to correctly identify lung nodules in each and every CT image without resorting to consensus voting.

The LIDC/IDRI dataset [24] includes 1018 cases, including medical annotations from 4 thoracic radiologists annotating chest CT images and an XML file for each test. In specifically, there are 7371 cases of nodules that have been segmented and diagnosed as injuries by at least one s

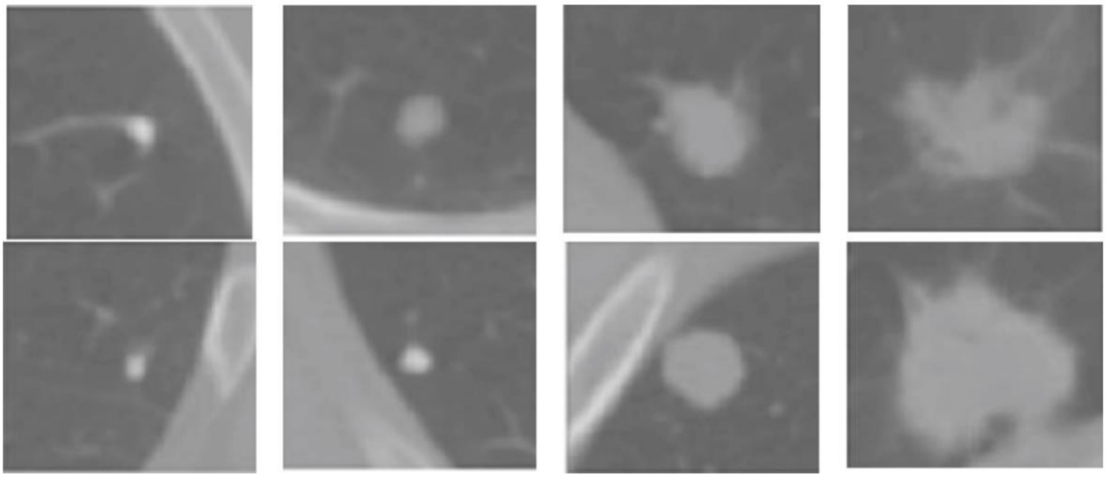


Figure 5- Examples of rated benign and malignant pulmonary nodules from the LIDC radiologist's marks [24]

pecialist, with 2669 of those nodules being designated as larger than 3 mm.

Figure 5 shows examples of benign and malignant lung nodules from the LIDC dataset arranged according to their malignancy grade.

4-2- The parameters' initialization

For assessing proposed algorithm quality, we set parameters based on base paper parameters [11]. In this way that 80 percent of the data were taken for training and 20 percent of data were taken for testing. Table 5.1 illustrates settings for proposed method parameters.

Table 2- Initial values for parameters in the proposed method

Parameters	Values
Training dataset	%80
Test dataset	%20
Image size	128*128
Number of layers	15
Learning rate	0.001
Maximum Epoch	2000

We will use more appropriate parameters of measurement for comparing presented solution with algorithms like neural networks. One of the criteria applied for illustrating data classification accuracy in algorithm of CNN is technique of finding value of accuracy.

The problem we're aiming to fix should guide our choice of criteria for assessing the efficacy of various methods. Assume you have access to a large number of data instances. One class is returned for each set of data given to the model. model-predicted class, and a subset of the data's possible representation in a table. The matrix of confusion is represented by the third table.

Table 3- The confusion table.

	The label of predicted class		
	predicted / real	healthy	sick
The label of actual class	healthy	*True negative (TN)*	*False positive (FP)*
	sick	*False negative (FN)*	*True positive (TP)*

True positive: instances which that have been detected accurately as patient by test.

False Positive: instances which have been detected falsely as patient by test.

True negative: instances which have been detected accurately as healthy by test.

False negative: instances which that have been detected falsely as healthy by test.

3.3.1 4-2-1- Sensitivity (Sn)

Sensitivity (Sn) is described as malignant nodules fraction greatly predicted as illustrated in Equation (1).

$$Sn = \frac{T_rP}{T_rP + F_aN} \tag{1}$$

3.3.2 4-2-2- specificity (Sp)

Specificity (Sp) is described as benign nodules fraction greatly predicted as illustrated in Equation (2).

$$Sp = \frac{T_r n}{T_r n + F_a p} \tag{2}$$

3.3.3 4-2-3- Classification accuracy (CA)

Test ability is accurately vary among healthy and sick cases from the other cases is known as accuracy. For computing test accuracy, sum true positive and negative samples ratio as well as sum of tested items should be achieved. Mathematically, the ratio could be stated as:

$$CA = \frac{T_r P + T_r n}{T_r P + \mathrm{T}_r n + F_a p + F_a N} \tag{3}$$

4-3- Evaluation of results

In this test, presented method is assessed by methods identified in papers [11], [8], [9], [10], CNN. For assessing these classifiers' performance, criteria of performance applied are sensitivity, accuracy, error rate, specificity. Ideally, good classification is expected to have high specificity, accuracy, sensitivity, and low rate of error. Table 4 measures different classifiers' specificity, accuracy, sensitivity, and error rates. As illustrated in Table 5-3, specificity, sensitivity, accuracy is presented for dataset of LIDC-IDRI. Average proposed accuracy value is 98 that is more than whole accessible work. In addition, average proposed method sensitivity is 97.06 that is higher than whole accessible works. Particular the proposed method is 99.15 that is the highest of whole accessible works. Thus, this could be concluded from Table 4 that presented method presents good outcomes in comparison with the other present works. Results of simulation illustrate that presented method accuracy has developed by 2.38 percent in comparison with main paper method [11].

Table 4- Results of comparison of the proposed method with existing methods

	Accuracy	Sensitivity	Specificity
Article Method [10]	%97.8	%97.1	%97.2
Article Method [9]	-	%79.6	%96.5
Article Method [8]	%96.2	%94.56	%94.2
Article Method [11]	%95.62	%97.93	%96.32
One CNN	85.66%	86.01%	84.62%
Proposed method	**%98**	**%99.15**	**%97.06**

5- Conclusion

The powerful deep learning CNN is applied. The convolutional neural network accuracy raises the depth, however causes an overexpression or blur gradient simultaneously. For solving the issue, we resort to the parallel CNN. The data used is the LIDC-IDRI consortium image collection has thoracic CT images that have been annotated for lung cancer diagnosis and screening purposes. Presented model includes models of CNN which integrate models results via set of methods and compare it with every model. Results of simulation illustrate that presented method accuracy has developed by 2.18 percent in comparison with main paper method.

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