

Original Research Paper

Detection of Pulmonary Nodules in ct Images Using Deep Learning Technique

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Abstract: Lung Cancer is one of the most deadly diseases worldwide. According to the American Cancer Society, about 234,030 peoples have been suffering from lung cancer. It can be cured if it is diagnosed earlier which decreases the death rate. A computational diagnostic tool named Computer Aided Diagnosis (CAD) is used to detect pulmonary nodules. Extensive work has been made in this domain. However, previous Computer Aided Diagnosis (CAD) system are time-consuming since they needed more modules such as image modification, segmentation and the features should be extracted by the domain experts to build the entire CAD system. It is hard to examine large data using the existing CAD system. Thus, a novel framework with a Convolutional Neural Network (CNN) to detect pulmonary nodule is proposed. Firstly, a preprocessing technique named bilateral filtering is applied to increase the image quality and remove the irrelevant noise from the Computer Tomography (CT) images. Secondly, the preprocessed data are trained into a convolutional neural network to detect the nodule and classify it. The performance of this system is validated using the Lung Image Database Consortium (LIDC) dataset. The accuracy of nodule candidate detection achieves 93%. It states that the proposed method achieves better accuracy in nodule detection.

Keywords: Lung Cancer, Computer Aided Diagnosis (CAD), Convolutional Neural Network (CNN)

Introduction

Cancer is a type of disease which damage cells in our body. There are various types of cell, which will cause different types of cancers in our body. Abnormal growth in the cells will cause cancer and it will grow rapidly. A set of cancer will form a tumor which will affect the normal healthy tissues.

There are two types of tumor cells which are classified as benign or malignant. The malignant tumors refer to cancer whereas benign tumors will not affect the other cells. Lung cancer has been classified into two types based on the size of the cell in microscopic appearance: Small Cell Lung Cancer (SCLC) and Non-Small Lung Cancer (NSCLC). It is classified. The stages of lung cancer can be classified based on how far it is spread. Thus early detection helps to increase the survival rate of the cancerous patients (Soo *et al.*, 2015; Aggarwal *et al.*, 2016).

At the early stage of diagnosis, radiologist used chest x-ray images in which small lung nodules were missed

which can be cancerous. Thus, instead of x-rays Computer Tomography (CT) scans are used.

Computer Aided Diagnosis (CAD) will decrease the observational overhead and false negative rates. It is a software that examines a radiographic image to detect specific disease. A recent study says that CAD assistance will improve the rate of nodule detection. A number of works has been going on in the performance improvement of CAD (Doi, 2007; Kadachha and Patel, 2012).

Several medical image databases are available which will contain CT images. It is a challenging task to eliminate noise from the medical images. In our approach, the noise will be reduced and the image quality will be improved by preprocessing.

Convolutional Neural Network (CNN) architecture consists of different layers namely: convolution layer, a pooling layer, a fully connected layer and a drop out layer (Le Cun *et al.*, 1998; Kuruvilla and Gunavathi, 2014). CNN allows several features to be extracted at each layer. In deep CNN features are extracted and learned hierarchically which can be formed by adding multiple hidden layers. CNN

Related Work

Several researchers have been published in the field of detection of lung cancer. Numerous approaches including image processing, machine learning algorithm have been employed by various authors. Some of these recent works have been discussed below.

Cascio *et al.* (2012) proposed a method for detecting the lung nodules automatically. The Lung Image Database Consortium (LIDC) database was used to evaluate the performance. Region growing and Stable 3D Mass-Spring Model (MSM) were used and achieved an accuracy of 88% and false detection rate of 12%.

Keshani *et al.* (2013) presented a lung nodule segmentation and recognition using Support Vector Machine (SVM) classifier and active contour modeling. LIDC database and ANODE09 were used to evaluate the performance. The lung area was segmented by active contour modeling and masking technique. In classification, SVM classifier was used. Their methodology reaches an accuracy of 89% and false detection rate of 11%.

Kuruvilla and Gunavathi (2014) presented a lung cancer classification using neural networks for CT images. In this work, initially segmentation was done using morphological operation and classification was done by both forward and back propagation network. In the LIDC database their work reached the accuracy of 93.3% and false detection rate of 6.7%.

Biradar and Agalatakatti (2015) presented a lung cancer identification using CT images. This work contains three modules. Preprocessing was done by median filter and segmentation done by the morphological operation. In classification SVM was used and reached an accuracy of 92% and false detection rate of 8% in the LIDC database.

Shyamala and Pushparani (2016) presented preprocessing and segmentation techniques for lung cancer on CT images. Preprocessing was done by median filter and segmentation is done by thresholding method and histogram equalization then texture features are extracted.

Rao *et al.*, (2016) presented a convolutional neural network for lung cancer screening in CT scans. They proposed a CNN technique for the analysis of CT scans with tumors. The accuracy of classification improved when compared to a traditional artificial neural network. They obtained accuracy was 76% and false detection rate of 24%.

Alakwaa *et al.* (2017) proposed detection and classification of lung cancer in the 3D neural network. Lung Nodule Analysis 2016 (LUNA 16) database was used to evaluate the performance. Initially, segmentation was done by thresholding and output was given into 3D CNN to classify them. This model reached an accuracy of 86.6% and false detection rate of 13.4%.

Xie *et al.* (2018) presented automated pulmonary nodule detection in CT images using deep CNN. In this work 2D convolutional neural network was proposed and boosting architecture based on 2D CNN was used to reduce false positive rate. Accuracy was reached 86.42% and false detection rate of 13.58%.

Proposed Method

The proposed CAD methodology depicted in Fig. 1 consists of the following steps: (1) acquisition of data (2) preprocessing (3) nodule detection.

Data Acquisition

CT image is preferred for lung cancer detection rather than other available medical images. There are many publicly available databases built to help the researcher. They can utilize those datasets for training and testing of their algorithms and models. Among those databases, most commonly used are LIDC, LIDC-IDRI and ANODE09 (Armato III *et al.*, 2011; Cascio *et al.*, 2012; Keshani *et al.*, 2013; Kuruvilla and Gunavathi, 2014; Biradar and Agalatakatti, 2015; Shyamala and Pushparani, 2016; Rao *et al.*, 2016).

LIDC is a publicly available database and it is working since 2001 for the development of CAD. It contains 1018 cases which is formed by seven academic centers and eight medical imaging companies. These data are divided based on three categories as shown in Fig. 2. They are:

- Nodule ≥ 3 mm
- Nodule < 3 mm
- Non-nodule ≥ 3 mm

LIDC-IDRI contains both CT and thoracic CT images. It contains screening and diagnostic thoracic CT scans and its associated metadata. It also contains different modalities images which will help the researchers (Armato III *et al.*, 2011).

Preprocessing

CT scans may contain some noise so that preprocessing is needed to improve quality. Preprocessing techniques are used in the removal of the noise and to increase the image quality. At first step contrast of the image will be increased and background noise will be reduced from the image. The result of the preprocessing technique is shown in Fig. 3 (Vijaya and Suhasini, 2014).

The bilateral filter is a nonlinear filter with a combination of two Gaussian filters used to smooth images (Tomasi and Manduchi, 1998; Olf and Nawres, 2014). The first filter works in the spatial domain and the next works in the intensity domain (Mohan and Sheeba, 2013). The output of the filter is a weighted average of the input. The bilateral filter is defined by:

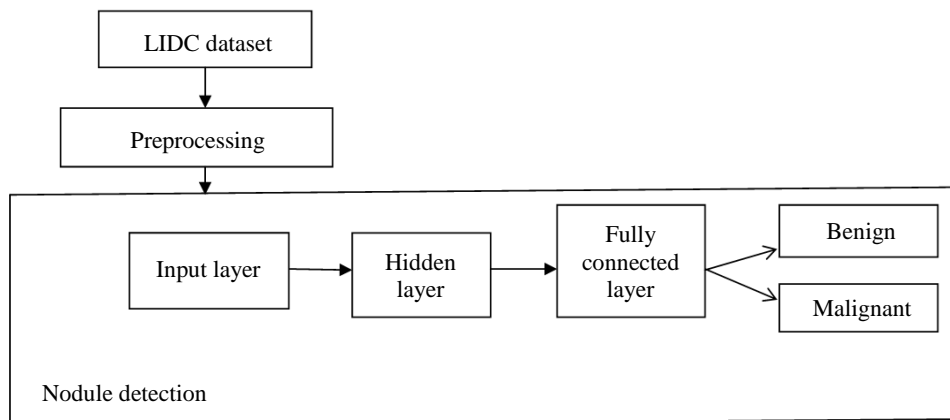


Fig. 1: Flow chart for the proposed CAD system

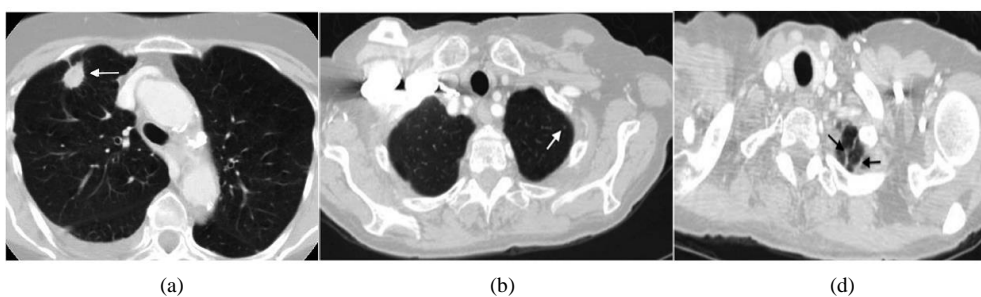


Fig. 2: Example of nodules (a) Nodule $\geq 3\text{mm}$; (b) Nodule $\leq 3\text{mm}$ (c) Non-nodule $\geq 3\text{mm}$

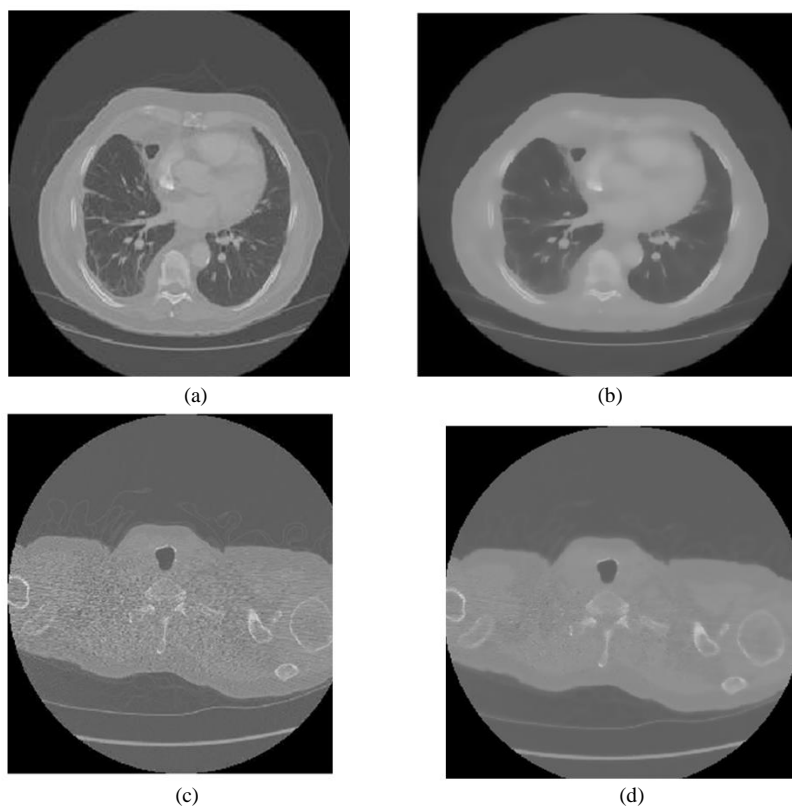


Fig. 3: (a) Normal nodule image (b) preprocessed nodule image (c) normal non-nodule image (d) preprocessed non-nodule image

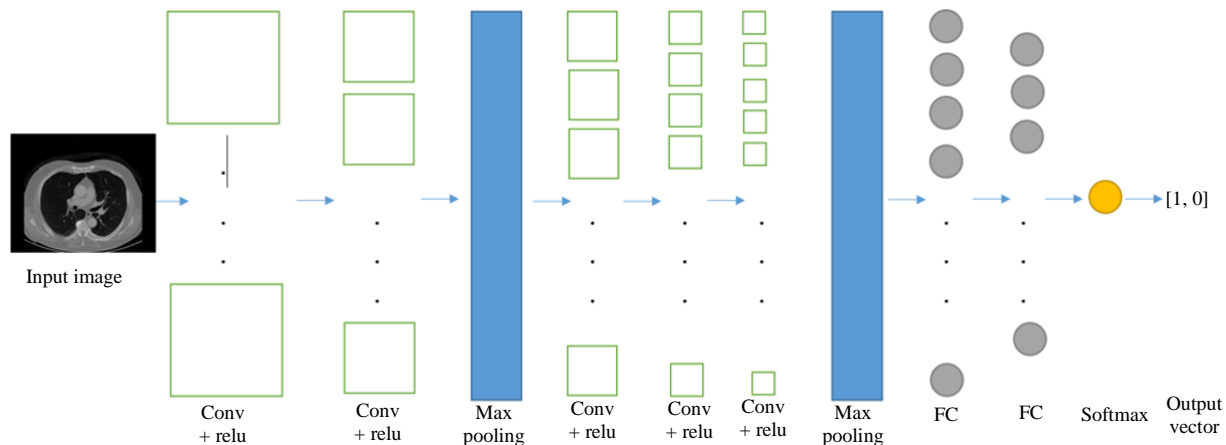


Fig. 4: Architecture of convolution neural network

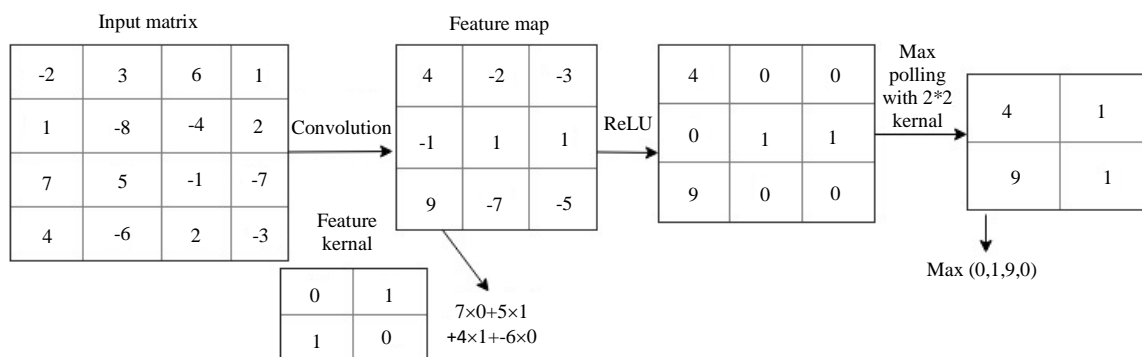


Fig.5: Working of layers

$$BF[I]_p = \frac{1}{W_p} \sum_{q \in s} G_{\sigma_s} (\|p - q\|) G_{\sigma_r} (\|I_p - I_q\|) I_q$$

Where:

- I_p = A pixel position $p = (p_x, p_y)$
- G_{σ} = Gaussian decreasing function
- σ_s and σ_r = The Gaussian standard deviations
- W_p = Normalizes the sum of the weights
- s = A spatial domain
- r = A range domain

Convolutional Neural Network (CNN) for Nodule Detection

CNN is a type of feed-forward neural network. A basic CNN consists of basic components namely input layer, convolution layer, activation function layer, pool layer and Fully Connected layer (FC). The architecture of the CNN is shown in Fig. 4. Input layer accepts the pixels of the image as input in the form of array.

Convolution layer computes dot product between all filters and image patch. The filter size can be a shape of

3*3. Next, the filter is shifted to other possible position and the above step is repeated until all pixels are processed at least once. The resulting matrix eventually detects the edges. Common activation function ReLU (Rectified Linear Units) will be applied to the output of the convolution layer. The purpose of this layer is to introduce nonlinearity to a system which just computes linear operations during the convolution layer. The ReLU layer applies the following function:

$$f(x) = \max(0, x),$$

It just changes all the negative activations to 0. Pooling layer is used for reducing the feature map dimensionality which gradually reduces the computational complexity of the model. There are different pooling techniques available such as max, min and average pooling. In this work, the max pooling is used to reduce the dimensionality. The max pooling layer will be operated on each activation map in the input which will reduce its dimensionality. Max function is used in which the kernel of dimension 2*2 applied with a stride of 2 along the spatial dimensions of the input.

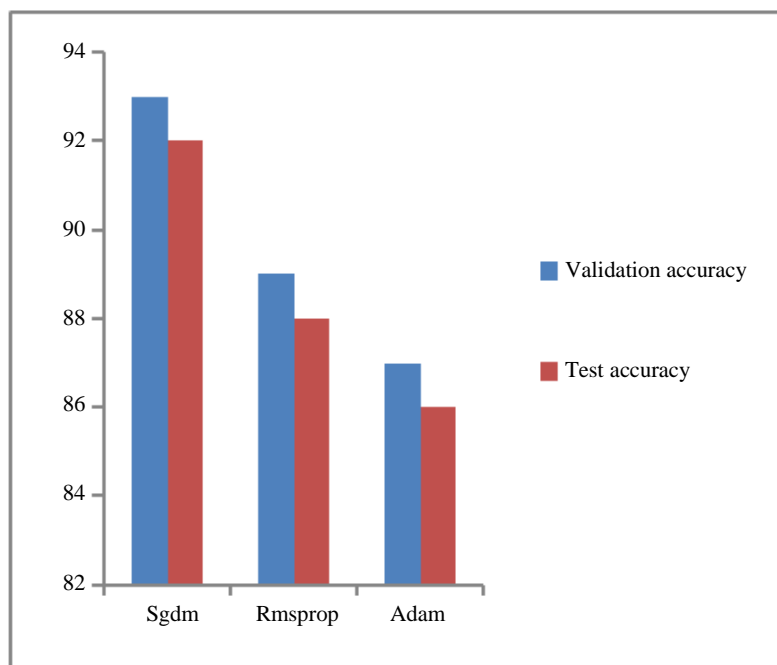


Fig. 6: Comparison of different optimization methods 'sgdm' 'rmsprop' and 'adam'

The input of the fully-connected layer will be taken from the previous layer. The fully-connected layer computes the class scores and outputs which will be in the form of one dimensional array that was equal to the size of the output class. Primarily the principal work of the weight kernel and pooling layer is to extract feature of the input images. The output layer it would connect all layers together to generate the output class. This layer changes the 2-dimensional features into one-dimensional vectors in the form of binary vector. The output of this layer is a label that can either be the predicted cancer or non-cancer. Fully-connected layer using a soft-max activation function is used to classify the features vector of the given image into a variety of classes based upon on the training data set. Figure 5 specifies the entire working of the layers.

The convolutional layer includes several parameters as input. The parameters were filters of size 3*3, with stride of 1. ReLu was used as the activation function. Max pooling with pool size [2, 2] was used. Dropout with the probability of 0.5 and fully connected layer.

In training, gradient descent related algorithms is used to optimize the deep network and non-convex loss function in nature. The Loss functions have many local minima which get simple cornered. In some cases, gradient is gone to vanish at non local optimum places is more issue than non-convex loss function. The variable 'Momentum' presented Stochastic Gradient Descent (SGD). It specifies the moment value using a momentum name value pair to the training image. The

drawback of this method is that it can assign parameters value based on how significantly updates are made. Another method called adaptive based gradient method 'Adagrad'. In this method, gradients are updated based on previous parameters. The updating gradients based on sparsity of parameters. Root Mean Square Propagation (RMSProp) could improve the drawbacks of Adagrad method by determining the weight on stable learning and improved performance in non convex loss function too. Figure 6 describes different optimization method 'SGDM' 'RMSPROP' and 'ADAM' with test accuracy and validation accuracy. During training, our Convnet architecture takes input as an image size 256*256 2D CT scans and their labels are provided where CT images with nodules are labeled as cancer and non-nodules as non-cancer. At each layer, features are extracted and the feature map is created to identify nodules. While training the network these maps get their labels and when testing data is given feature get identified and classified based on labels.

Results and Discussion

The proposed method was implemented in MATLAB R2018b. In this method, the networks were trained with the Stochastic Gradient Decent Momentum (SGDM) optimization technique with the initial parameters. We set each of the parameters as (Maximum Number of Iteration: 4, Mini Batch Size: 4, Initial learning rate:

0.0001 and the Verbose Frequency:1). Batch normalization layer and Rectified Linear Unit activation function has been added after each of the convolution 2D layer which makes the training progress faster even for a large amount of data.

The efficacy of the proposed system has been evaluated using different metrics. The output of the system was assessed independently. This proposed method is compared with the ground truth of the clinical images. Evaluation metrics includes Accuracy, Sensitivity and Specificity is calculated using the confusion matrix is shown in Table 1. The confusion matrix comprised of actual and predicted values of positive and negative. In the medical diagnostic test, the presence of disease is positive whereas negative is an absence of disease.

The metrics are defined as follows:

$$\text{Accuracy} = \frac{TP}{TP + TN + FP + FN}$$

$$\text{Sensitivity} = \frac{TP}{TP + FN}$$

$$\text{Specificity} = \frac{TN}{TN + FP}$$

Where:

TP = represents True Positive, where result is positive in case of malignant

TN = Represents True Negative; where result is negative in case of benign

FN = Represents False Negative; where result is negative in case of malignant

FP = Represents False Positive; where result is positive in case of benign

500 images (250 malignant, 250 benign) from the dataset have been undergone this proposed architecture for preprocessing, detection and classification of nodules. 250 images (125 malignant, 125 benign) are used for training and 250 images (125 malignant, 125 benign) are used for testing the proposed system. The confusion matrix for proposed method is shown in Table 2. The proposed system obtained the accuracy of 92.77%, sensitivity of 96.75% and specificity of 95.28%.

In the Fig. 7a and 7b, blue line specifies the training accuracy and the red line specifies the validation accuracy. In Fig. 7a, there is an increase in accuracy but also there is an increase in loss as iteration increases. In Fig. 7b, there is a steady increase in accuracy and decrease in the loss as the iteration increases. The proposed methodology outperforms the existing work is depicted in Table 3.

Table 1: Confusion matrix

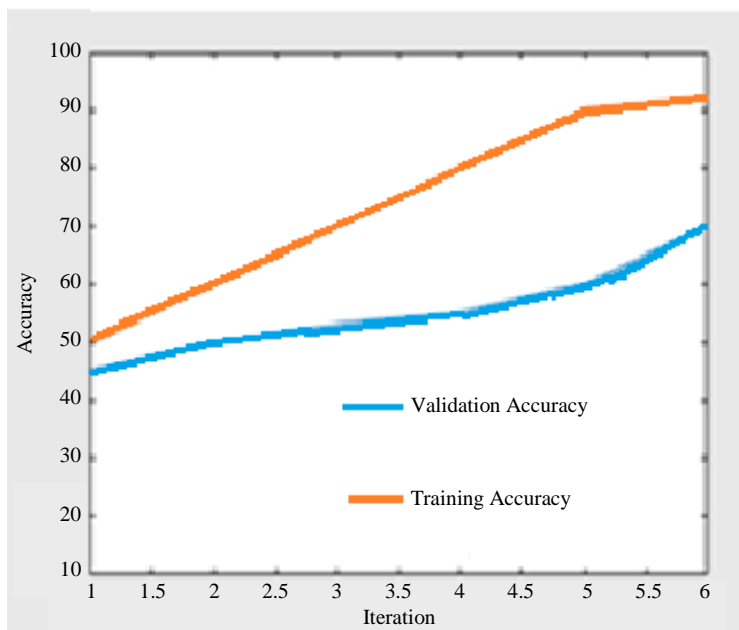
Actual	Predicted	
	Positive	Negative
Positive	TP	FP
Negative	FN	TN

Table 2: Confusion matrix using proposed method

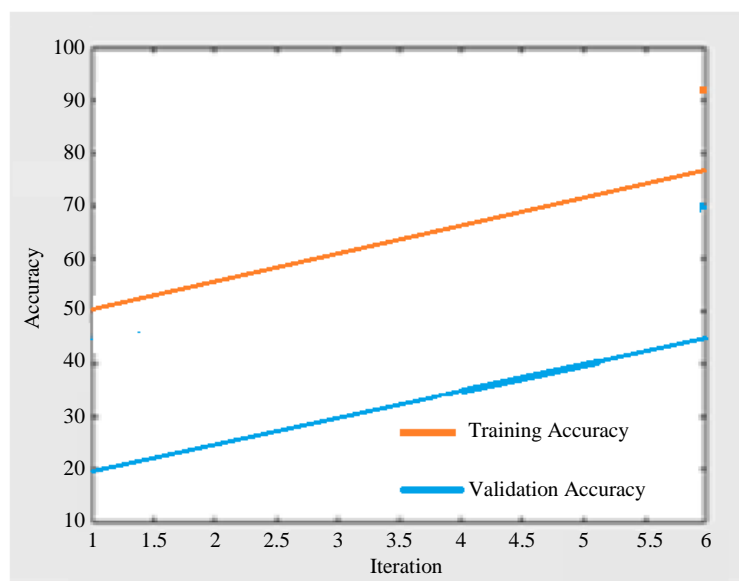
Actual	Predicted	
	Malignant	Benign
Malignant	119	6
Benign	4	121

Table 3: Comparison with previous works

Author	Database	Algorithms used	Accuracy (%)
Cascio <i>et al.</i> (2012)	LIDC	Region growing 3DMass-Spring Model (MSM)	88
Keshani <i>et al.</i> (2013)	LIDC ANODE09	Active contour modeling Masking technique SVM classifier	89
Kuruvilla and Gunavathi (2014)	LIDC	Morphological operation Backward propagation network (BPN)	91
Biradar and Agalatakatti (2015)	LIDC	Median filter morphological operation SVM classifier	88
Rao <i>et al.</i> (2016)	LIDC	Convolutional neural network (CNN)	76
Alakwaa <i>et al.</i> (2017)	LUNA16	Thresholding 3D CNN	86.6
Xie <i>et al.</i> (2019)	LIDC	2D CNN	86.42
Proposed Method	LIDC	Bilateral filtering convolution neural network	93



(a)



(b)

Fig.7: (a) Accuracy vs Iteration for simple CAD (b) Accuracy vs Iteration for CAD with preprocessing

Conclusion

We have developed a CAD system to detect the nodules in CT images. Experiments were designed to preprocess the CT images to remove the noise and train it into the architecture to detect the nodule and classify it based on the labels. The performance of the CAD system without preprocessing and the proposed architecture was evaluated. Experimental results demonstrated that our proposed CAD system yielded the best performance. The maximum classification accuracy of 93% is achieved. In the future, different layers will be included and some

optimization technique can be added to improve the performance of the system.

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Author's Contributions

All authors are equally contributed in this work and this paper.

Santhi Balachandran: Planned and carried out the experiments.

Divya: Participated in data collection and feature selection.

Nithya Rajendran: Participated in performance evaluation.

Brindha Giri: Participated in Related work.

Ethics

This article is original and contains unpublished material. The corresponding authors have read and approve the manuscript and no ethical issues involved.

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