Bat Algorithm with CNN Parameter Tuning for Lung Nodule False Positive Reduction

R. R. Rajalaxmi(✉), K. Sruthi, and S. Santhoshkumar

Kongu Engineering College, Perundurai, India
rrrkec.69@gmail.com, ksruthicit@gmail.com, santhosh@kongu.edu

Abstract. Lung cancer, an uncontrolled development of abnormal cells in one or both lungs has been one of the primary causes of cancer related deaths worldwide. Detecting it in the earlier stage is the only solution to reduce lung cancer deaths. The most common tests to look for cancerous cells include X-ray, CT scan, Sputum cytology and biopsy test. CT scan is recognized as one of the effective tools in recognizing it in the earlier stage. Detecting the lung nodules (lesions) sometimes seems to be very difficult in Computer Aided Detection (CAD) systems. Because of the fact that the lung nodules have similar contrast with other structure, there might be a chance in generating numerous false positives. The performance of Convolutional Neural Network (CNN) mainly depends on the hyper parameters selected for a problem. The main motive of the proposed work is to use Bat algorithm to optimize the network hyper parameters such as number of filters in convolution layers, number of neurons and filter size in the CNN to enhance the network performance thereby eliminating the requirement of manual search for optimal hyper parameters. The methodology is validated using important performance validation metrics such as accuracy, sensitivity and specificity. The result shows that CNN in conjunction with Bat algorithm provides better results in the classification of nodules and non-nodules with minimal false positive rate.

Keywords: Deep learning · Lung nodules · Convolutional Neural Network · Bat algorithm · Particle swarm optimization · Hyper parameter

1 Introduction

Deep learning aims in creating artificial neural networks, capable of learning and taking the decisions intelligently with the help of algorithms. Deep learning uses neural networks with several layers of nodes between the input and output layer. Term deep here refers to the number of layers in the network i.e. the more the layers, the deeper the network. Series of layers between input and output perform feature identification. The need for deep learning raised mainly to process huge volume of data, perform complex algorithms, to achieve best performance with large amount of data and for effective feature extraction [10].

Deep learning in health care covers a wider range of problems ranging from cancer screening and disease monitoring to providing personalized treatment suggestions.

A. Chandrabose et al. (Eds.): ICCIDS 2020, IFIP AICT 578, pp. 131–142, 2020.
https://doi.org/10.1007/978-3-030-63467-4_10

Immense amount of data is present from radiological imaging such as X-ray, CT and MRI scans. There is shortage of tools to convert all this data to useful information.

Lung cancer is one of the life-killing dreadful diseases in the developing countries. Computed Tomography (CT), Sputum Cytology, Chest X-ray and Magnetic Resonance Imaging (MRI) are some of the medical imaging techniques employed in the earlier detection of lung cancer. Here, detection means classifying tumour basically into two classes one is noncancerous tumour which is also known as benign and the other one is cancerous tumour which is also referred as malignant. There is very less chances of survival of a lung cancer patient at the advanced stage when compared to the one when diagnosed and treated at the early stage of the cancer.

Deep neural network plays an important role in the recognition of the cancer cells among the normal tissues, thereby providing an effective tool for building an assistive Artificial Intelligence based cancer detection. The cancer treatment will be effective only when the malignant cells are accurately separated from the normal cells. Classification of the tumour cells followed by training of the neural network forms the basis for the deep learning-based cancer detection.

2 Related Works

Andreas Maier and others [9] provided a gentle introduction to deep learning in medical image processing, proceeding from theoretical foundations to applications. The proposed paper discusses about the reasons for the popularity of deep learning, reviews the fundamental basics of perceptron and neural network. It also discusses about medical image processing particularly in image detection and recognition, segmentation, registration and computer aided diagnosis.

A new method of using three-dimensional (3-D) convolutional neural networks (CNNs) for FP reduction in automated pulmonary nodule detection from volumetric CT scans is addressed in the work [2]. The importance and effectiveness of integrating multilevel contextual information into 3-D CNN framework for lung nodule detection in volumetric CT data is discussed using the experimental results.

The authors [3] presented a novel approach, which is Fast and Adaptive Detection of Pulmonary Nodules in Thoracic CT Images Using a Hierarchical Vector Quantization Scheme in which combination of custom rule-based filtering operations, extraction of features, and SVM classifier is employed.

A CAD system that uses deep features extracted from an auto encoder to classify the lung nodules into nodules and non nodules is suggested in the work [5].10 fold cross validation is used for which the results obtained are 75.01% accuracy with a sensitivity rate of 83.35%.

Haeil Lee and others [6] pointed out an approach of using Gaussian weighted average image patches for contextual Convolutional neural networks for lung nodule classification. With the extracted patches, 2D CNN is trained to achieve the classification of lung nodule candidates into positive and negative labels.

A dedicated proposal on survey on deep learning in medical image processing is clearly illustrates about how deep learning algorithms are effectively used for analyzing medical images [7].

The authors [8] used 62,492 slices of nodule-candidates extracted from 1013 CT scans obtained from the LIDC-IDRI database, containing 40,772 nodules and 21,720 non-nodules. The test scheme was designed using two separate strategies. The first was 10-fold cross-validation, and the other was the database division into training data (85.7%) and testing data (14.3%). Five tests were performed with various configurations, hyper parameters, and image sizes and achieved optimal results of 84% of accuracy.

Cascaded CNNs are used [11] to perform as selective classifiers for filtering out apparent non-nodules such as blood vessels or ribs in each cascading stage. To implement such selective classifiers, the CNNs are trained with an inverse imbalanced data set consisting of numerous nodule images and a few non-nodule images. The method was tested on 1348 nodules and 551,062 non-nodules in 888 CT scans obtained from the Lung Nodule Analysis (LNA) database.

Santos and others [12] introduced a methodology for automatic detection of small lung nodules (with sizes between 2 and 10 mm) and performed FP reduction at the end. Tsalli's and Shannon's entropy indexes were used as texture descriptors and SVM to classify suspect regions as either nodules or non-nodules.

A hierarchical learning framework, i.e. Multi-scale Convolutional Neural Networks (MCNN)-is suggested by the authors [13] in order to capture nodule heterogeneity by extracting discriminative features. The methodology was evaluated on CT images from Lung Image Database Consortium and Image Database Resource Initiative (LIDC-IDRI), where both lung nodule screening and nodule annotations are provided.

A new approach based on automated detection of solitary pulmonary nodules using Positron Emission Tomography (PET) and Computed Tomography is presented in the work [14]. An improved false positive (FP) reduction method is identified for the detection of lung nodules in PET/CT images by means of Convolutional Neural Networks (CNNs).

The methodology proposed by Taşci and Ugur [15] used 33 features based on shape and texture information extracted from nodule candidates, and realized tests with four methods of feature selection. The optimum subset is identified by evaluating classifier performance on the top five classifiers among the 10 which is tested based on the area under the ROC curve (AUC).

A new technique of using deep feature fusion from the non-medical training and hand-crafted features is presented by Changmiao and others [16] in order to reduce the false positive results. The experimented result showed 69.3% of sensitivity and 96.2% of specificity.

Semi supervised adversarial model classification (SSAC) of lung nodule on chest CT images has been introduced by Xie and others [17]. This model consists of two networks namely an adversarial autoencoder-based unsupervised reconstruction network and a supervised classification network, and also learnable transition layers. The SSAC model has been extended to the Multi-view Knowledge-based collaborative learning, aiming to employ three SSACs to characterize each nodule's overall appearance, heterogeneity in shape and texture and also to perform such characterization on nine planar views. The model has been evaluated on the widely used benchmark LIDC-IDRI dataset.

Kaur and Sharma [4] proposed a dedicated survey on using nature inspired computing for fatal disease diagnosis. This proposal effectively analyses the efficacy of various nature inspired techniques in diagnosing diverse critical human disorders. The article explains how Genetic Algorithm, Ant Colony Optimization, Particle Swarm Optimization and Artificial Bee Colony optimization have been successfully used in early diagnosis of different diseases. Furthermore, ACO, PSO and ABC are found to be best suited in diagnosing lung, prostate and breast cancer respectively.

Da Silva and others [1] proposed a new model PSO Algorithm with Convolutional Neural Network to evaluate the optimal values of the CNN and to reduce the classification error. This paper presents a methodology for reduction of lung nodule false positive on CT scans.

Nature provides rich models to solve these problems and hence swarm intelligence optimization algorithm has been introduced. The bat algorithm (BA) was proposed by professor Yang based on the swarm intelligence heuristic search algorithm in 2010 and is a kind of effective method to search the global optimal solution. BA has attracted more and more attention because of its simple, less parameters, strong robustness, and the advantage of easy implementation. Therefore, the Bat algorithm is used to optimize a few of the hyper parameters in CNN model, eliminating the requirement of a manual search to identify the optimal hyper parameters for the classification of nodule and non-nodules.

3 Problem Statement

Lung cancer identification is difficult and an extremely complex problem to solve. However, if it is detected in early stage, the patient has a high chance of survivability. The diagnostics data suggests that the highest degree of people who get diagnosed with this type of cancer have already an advanced form of cancer.

4 Proposed Method

The main objective of the proposed work is to classify the CT images into nodules and non-nodules using a CNN in conjunction with the Bat algorithm to optimize the network hyper parameters. With the obtained optimized hyper parameter values, the sensitivity rates can be increased there by efficiently reducing the number of false positives.

The proposed methodology is divided into three steps as described in Fig. 1. To be explained briefly, the first step deals with the preparation of images for lung cancer identification. The second step is the classification into nodules and non-nodules using CNN-based Bat, further followed by result evaluation.

4.1 Dataset Details

The image database used in this research is the pre-processed 50×50 LIDC-IDRI image dataset. The dataset was divided into three sets: training, validation and test set. Table 1 depicts the distribution of the data set.

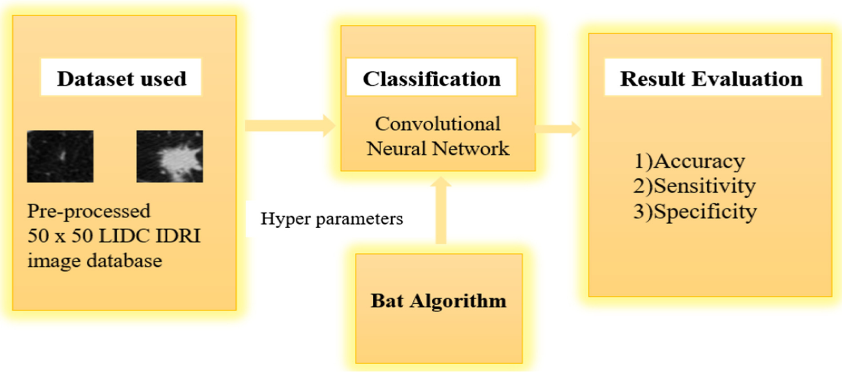

Fig. 1. Proposed methodology

Table 1. Dataset details

Dataset	No. of nodule candidates	No. of non-nodule candidates	Total
Training data set	845	4342	5187
Validation dataset	224	1063	1287
Test data set	182	1318	1500
Total	1251	6723	7974

4.2 Classification Using CNN

The preprocessed CT grey scale images of size 50 × 50 is submitted to CNN to classify the images into nodule and non-nodules. Figure 2 depicts the CNN architecture. The architecture consists of two convolutional layers with ReLU activation (C1 and C2), two max pooling layers (P1 and P2) after each convolutional layer followed by a dropout layer.

The completely connected layer presents an input layer, a hidden layer followed by ReLU activation and dropout layer and an output layer with sigmoid activation. The total number of filters used in first and second convolutional layers are 32, size of trainable filters are 3 in each convolutional layers C1 and C2, batch size of 32, max pooling is used in the pooling layers with pool size 2 × 2,128 neurons in the hidden layer, the probability of dropout in convolutional layer is 0.35 and probability of dropout used in completely connected layer is 0.04.

4.3 Convolutional Neural Network with Bat Architecture

The performance of plain CNN model purely depends on the network hyperparameters that are assigned manually. In order to obtain optimized hyperparameter value metaheuristic approach can be used to enhance the performance of the network and to eliminate manual search. In the proposed work Bat algorithm, one of the effective metaheuristic methods is used for hyperparameter tuning.

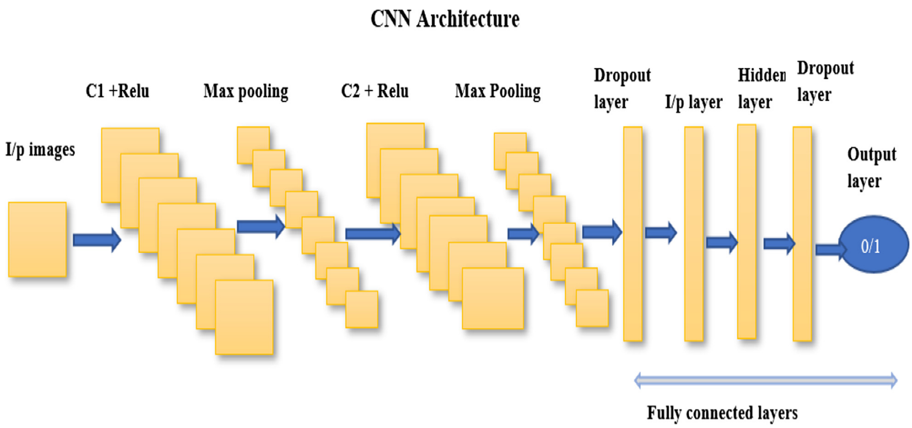

Fig. 2. CNN architecture

In the beginning, the Bat parameters such as number of bat population, maximum number of iterations, upper bound, lower bound, dimension, loudness, pulse rate, maximum and minimum frequency range are initialized as depicted in Table 2. The four parameters in CNN that has to be tuned using Bat algorithm are Number of filters in first and second convolution layer, number of neurons in the hidden layer and filter size. The bat algorithm randomly initializes these hyper parameters based on the upper and lower bound specified in parameter initialization process. The upper and lower bound values for number of filters in first and second convolution layer, number of neurons in the hidden layer are randomly initialized with integer values between 4–100. The filter size is initialized with integer values 3, 5 or 7.

Table 2. Bat-Parameters for initialization

Parameters	Values
Dimension	4
Iterations	3
Bat population	3
Loudness	0.5
Pulse rate	0.5
Minimum and maximum frequency	0.0–0.2

The fitness of each bat is evaluated using the following equation:

$$\text{Fitness} = (2 - 2 * \text{Sensitivity}) + (1 - \text{Specificity}) + (1 - \text{Accuracy}) \tag{1}$$

A higher weight is assigned to the metric sensitivity in order to obtain models with a high capacity to classify nodules correctly. In this way we tend to reduce false positive rates.

Bat Algorithm

```
Initialize the bat population x_i and v_i (i=1, 2….n)
Initialize frequencies f_i , pulse rates r_i and loudness A_i ---#Min and Max frequency
(0.0-0.2)
#Pulse rate and loudness= 0.5
While (t<Max number of iterations)
  Generate new solutions by adjusting frequency
   Update velocities and locations/solutions
    if(rand> r_i )
          Select a solution among the best solutions
          Generate a local solution around the selected best solutions based on
          fitness.
     endif
    Generate a new solution by flying randomly
    if(rand< A_i & f(x_i) < f(x*))
           Accept the new solutions
           Increase r_i  and reduce A_i
    end if
    Obtain the fitness for the three bats
     Rank the bats based on minimum fitness value and find the best bat
  End while
```

The process flow of Bat-CNN is depicted in Fig. 3

Once the terminating criteria is satisfied, the best bat with minimum fitness is obtained by ranking the bats based on minimum fitness as mentioned in Eq. 1. The parameter values for the best bat initialized by bat algorithm are obtained. The best parameter value will be the optimal hyper parameter value for the CNN architecture. The optimized result obtained are 48 filters in first convolutional layer, 90 filters in second convolutional layer, 78 neurons in the hidden layer and filter size of 7.

4.4 Convolutional Neural Network with Particle Swarm Optimization

Since the dataset used is pre-processed lung image datasets a comparison is made with another effective nature inspired algorithm, Particle Swarm Optimization algorithm. PSO is another meta heuristic approach to obtain optimized hyper parameter value to enhance the performance of the network. The same 50 × 50 preprocessed lung CT scan images which is used in CNN based Bat architecture is submitted to CNN based PSO architecture. Initially, the PSO parameters such as swarm size, maximum number of iterations, upper bound, lower bound, dimension, cognitive parameter, social parameter and inertia weight are initialized as depicted in Table 3

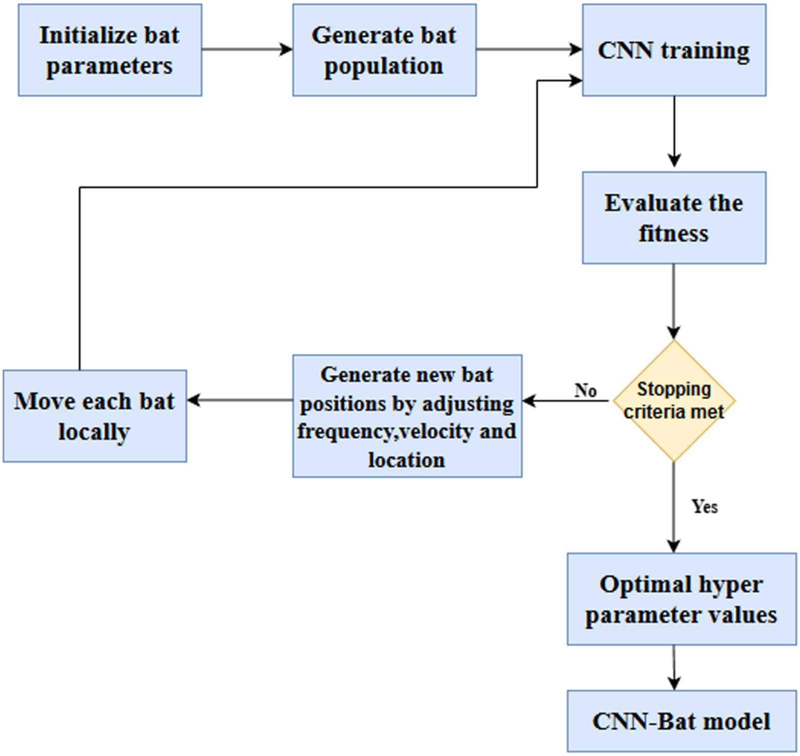

Fig. 3. Process flow of Bat-CNN

Table 3. PSO-Parameters for initialization

Parameters	Values
Dimension	4
Iterations	3
Swarm size	3
Cognitive parameter	2.0
Social parameter	2.0
Inertia weight	0.7

The four parameters in CNN that has to be tuned using PSO algorithm are the number of filters in first and second convolution layer, number of neurons in the hidden layer and filter size. The upper and lower bound values for number of filters in first and second convolution layer, number of neurons in the hidden layer are initialized with integer values between 4–100. The filter size is initialized with integer values 3, 5 or 7.

The fitness of each PSO is evaluated using the following equation:

$$\text{Fitness} = (2 - 2 * \text{Sensitivity}) + (1 - \text{Specificity}) + (1 - \text{Accuracy}) \tag{2}$$

PSO Algorithm

Initialize the objective function
For each particle
 For each dimension
  Initialize position x_i and velocity v_i
 While
  For loop over all n particles and d dimensions
  Generate new velocity vi^{t+1}
  Calculate new local solutions $xi^{t+1} = xi^{t+1} + vi^{t+1}$
  Calculate the fitness function value as mentioned in equation 2
  Find the current best value for each particle xi^*
   If the fitness value is better than xi^* in the past history
    Set current fitness value as Xi^*
   End for
   Find the current global best g^* by choosing the value with best fitness value
   Update t=t+1(pseudo time or iteration counter)
End while
Output the final result xi^* and g^* (Obtain local and global best results which is the optimal hyperparameter)

Each particle is attracted towards the position of the current global best g^* and its best position xi^*. When the particle finds a location that is better than any previously found locations, the particle updates the location as the new current best for particle i. In the similar way the current best for all n particles at any time t is obtained. The aim is to find the global best among all the current best solutions until the objective no longer gets improved further or after certain number of iterations. Figure 4 illustrates the process flow of PSO-CNN.

The optimized hyperparameter value obtained using PSO algorithm are 100 filters in first convolutional layer, 44 filters in second convolutional layer, 100 neurons in the hidden layer and filter size of 7.

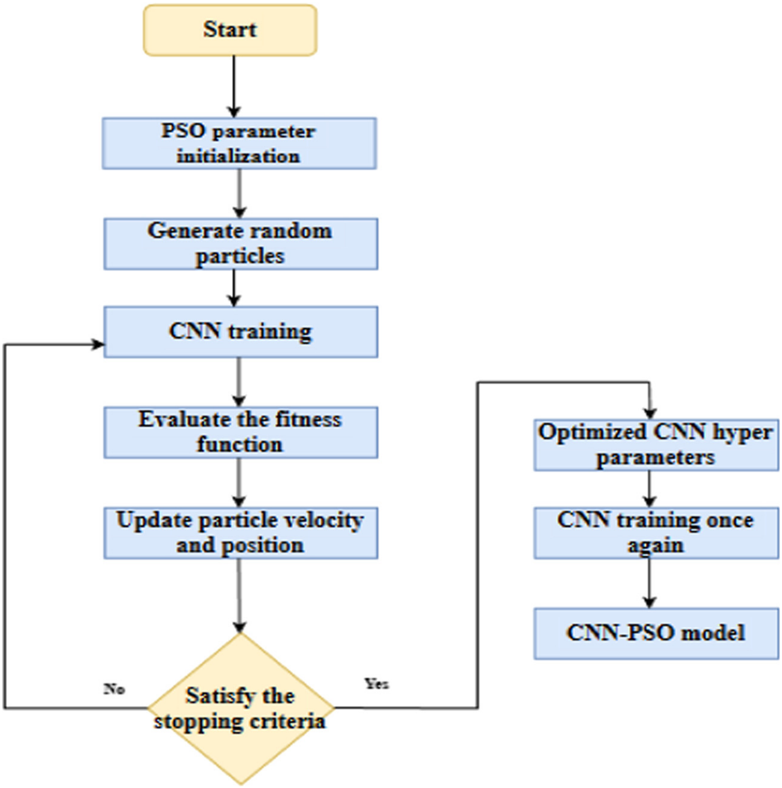

Fig. 4. Process flow of PSO-CNN

5 Experimental Results and Discussion

This section presents and discuss the results obtained with the proposed methodology with reference to lung nodule false positive reduction on CT scans. The entire methodology was implemented in python code using Keras deep learning library and executed on Kaggle GPU and GPU.

Comparison of test accuracy, sensitivity, specificity between plain CNN model, Bat based CNN model, PSO based CNN model is made and the results are depicted in Table 4.

Thus, CNN based Bat algorithm significantly increased the test accuracy, sensitivity and specificity compared to CNN based PSO. With the increased sensitivity rates, the total number of false positives can be reduced. Even though similar works [1] have been done to improve lung nodule classification, Bat algorithm is implemented with reduced datasets. However, the result depicts that the Bat algorithm can provide good results for high dimensional datasets. It is noticed that the feature extracted by the proposed model from the images are indistinguishable between nodule and non-nodule images in some cases. Due to this the model classifies few of the nodule images as non-nodules. The number of hidden layers may be increased to extract the low-level features.

Table 4. Comparative study-plain CNN model, CNN based PSO and CNN based Bat algorithm

Parameters	Plain CNN model	CNN with Bat	CNN with PSO
No. of filters in C1	32	48	100
No. of filters in C2	32	90	44
Number of neurons in hidden layer	128	78	100
Filter size	3	7	7
Sensitivity	0.8120	0.8368	0.8104
Specificity	0.8528	0.9271	0.8612
Accuracy	0.8456	0.9112	0.8504

6 Conclusion

Parameter selection for Convolutional Neural Network is one of the most important problems. Nature inspired algorithm, one of the optimization techniques can provide some efficient results. Bat Algorithm is used for adjusting the CNN parameters to find the optimal CNN hyper parameters. In the proposed work, Bat Algorithm with Convolutional Neural Network is used for controlling the parameter values which gives the better solution by exploring and exploiting. The result shows that the Bat Algorithm with Convolutional Neural Network achieved better classification accuracy, sensitivity and specificity in classifying nodule and non-nodules compared with CNN based PSO and plain CNN models. Thus, better sensitivity results in reduced false positive rates. In future, CNN architecture can be experimented in conjunction with other nature inspired algorithms in order to optimize the parameter values and try to achieve good classification results. The proposed methodology simply classifies CT images into the nodules and non-nodules but does not specify the stages of lung cancer. Future work can be performed on specifying the stages such as initial, moderate and severe cases.

References

1. Da Silva, G.L.F., Valente, T.L.A., Silva, A.C., de Paiva, A.C., Gattass, M.: Convolutional neural network-based PSO for lung nodule false positive reduction on CT images. Comput. Methods Programs Biomed. **162**, 109–118 (2018)
2. Dou, Q., Chen, H., Yu, L., Qin, J., Heng, P.A.: Multilevel contextual 3-DCNNs for false positive reduction in pulmonary nodule detection. IEEE Trans. Biomed. Eng. **64**(7), 1558–1567 (2016)
3. Han, H., Li, L., Han, F., Song, B., Moore, W., Liang, Z.: Fast and adaptive detection of pulmonary nodules in thoracic CT images using a hierarchical vector quantization scheme. IEEE J. Biomed. Health Inf. **19**(2), 648–659 (2014)
4. Kaur, P., Sharma, M.: A survey on using nature inspired computing for fatal disease diagnosis. Int. J. Inf. Syst. Model. Design (IJISMD) **8**(2), 70–91 (2017)
5. Kumar, D., Wong, A., Clausi, D.A.: Lung nodule classification using deep features in CT images. In: 12th Conference on Computer and Robot Vision, pp. 133–138. IEEE, June 2015

6. Lee, H., Lee, H., Park, M., Kim, J.: Contextual convolutional neural networks for lung nodule classification using Gaussian-weighted average image patches. In: Medical Imaging 2017: Computer-Aided Diagnosis, vol. 10134, p. 1013423. International Society for Optics and Photonics, March 2017
7. Litjens, G., et al.: A survey on deep learning in medical image analysis. Med. Image Anal. **42**, 60–88 (2017)
8. Li, W., Cao, P., Zhao, D., Wang, J.: Pulmonary nodule classification with deep convolutional neural networks on computed tomography images. Comput. Math. Methods Med. **2016**, 1–7 (2016)
9. Maier, A., Syben, C., Lasser, T., Riess, C.: A gentle introduction to deep learning in medical image processing. Zeitschrift für Medizinische Physik **29**(2), 86–101 (2019)
10. Pandey, S.K., Janghel, R.R.: Recent deep learning techniques, challenges and its applications for medical healthcare system: a review. Neural Process. Lett. **50**(2), 1907–1935 (2019). https://doi.org/10.1007/s11063-018-09976-2
11. Sakamoto, M., Nakano, H.: cascaded neural networks with selective Classifiers and its evaluation using lung x-ray CT images. arXiv preprint arXiv:1611.07136 (2016)
12. Santos, A.M., de Carvalho Filho, A.O., Silva, A.C., de Paiva, A.C., Nunes, R.A., Gattass, M.: Automatic detection of small lung nodules in 3D CT data using Gaussian mixture models, Tsallis entropy and SVM. Eng. Appl. Artif. Intell. **36**, 27–39 (2014)
13. Shen, W., Zhou, M., Yang, F., Yang, C., Tian, J.: Multi-scale convolutional neural networks for lung nodule classification. In: Ourselin, S., Alexander, Daniel C., Westin, C.-F., Cardoso, M.J. (eds.) IPMI 2015. LNCS, vol. 9123, pp. 588–599. Springer, Cham (2015). https://doi.org/10.1007/978-3-319-19992-4_46
14. Teramoto, A., Fujita, H., Yamamuro, O., Tamaki, T.: Automated detection of pulmonary nodules in PET/CT images: ensemble false-positive reduction using a convolutional neural network technique. Med. Phys. **43**(6Part1), 2821–2827 (2016)
15. Taşcı, E., Uğur, A.: Shape and texture based novel features for automated juxta pleural nodule detection in lung CTs. J. Med. Syst. **39**(5), 46 (2015)
16. Wang, C., Elazab, A., Wu, J., Hu, Q.: Lung nodule classification using deep feature fusion in chest radiography. Comput. Med. Imaging Graph. **57**, 10–18 (2017)
17. Xie, Y., Zhang, J., Xia, Y.: Semi-supervised adversarial model for benign–malignant lung nodule classification on chest CT. Med. Image Anal. **57**, 237–248 (2019)