Oncology Case Reports Journal

Review Article
Published: 10 Apr, 2023

Early Prediction and Classification of Lung Nodule Diagnosis on CT Images with Machine Learning Techniques - A Brief Review

Vijay KG[1] and Balaji S[2]*

[1]Department of Computer Science & Engineering, Koneru Lakshmaiah Education Foundation, Deemed to be University, India

[2]Department of Computer Science & Engineering, Koneru Lakshmaiah Education Foundation, Deemed to be University, India

Abstract

This paper presents a Computer-Aided Detection (CAD) system based on the acquisition of Three-Dimensional (3D) behavior to detect nodules in the lungs. The CAD provides useful second feedback and eliminates distinctions between visitors. In this paper, they present a computer system designed to detect lung nodes. It uses two different multi-level schemes to identify the lung field and separate candidate sets at high sensitivity speeds. The main task of this work is to classify the components into a highly balanced candidate set using Support Vector Machines (SVMs). The basic techniques used in lung nodes are pre-processing, division, characterization, and classification. Feed forward Neural Networks (NNs), SVMs, end trees (TDs), and Linear Discrimination Analysis (LDAs) were used to determine ROI. Synthetic neural networks and auxiliary Vector Machines (SVM) models are widely used in taxonomy for their ability to model complex systems. Imaging techniques can be useful for radiologists to im-prove the detection of lung nodes. The results show CNN (97.4%), SVM sensitivity (96.5%), and DNN (97.8%) specificity over other classifiers.

Keywords: Lung nodule; Prediction; Classification; Preprocessing; Segmentation; Future extraction; Deep learning; Machine learning

***Correspondence:**
Vijay Kumar Gugulothu, Department of Computer Science & Engineering, Koneru Lakshmaiah Education Foundation, Deemed to be University, Telangana, India,
E-mail: vijaykumargugulothu@klh.edu.in

Received Date: *07 Mar 2023*
Accepted Date: *05 Apr 2023*
Published Date: *10 Apr 2023*

Citation:
Vijay KG, Balaji S. Early Prediction and Classification of Lung Nodule Diagnosis on CT Images with Machine Learning Techniques - A Brief Review. Oncol Case Report J. 2023; 6(1): 1055.
ISSN: 2641-9173

Introduction

In most countries, lung cancer is the leading cause of death for both sexes. Early diagnosis has significant diagnostic value, which has a huge impact on the treatment plan [1]. Since nodules are a common symptom of lung cancer, finding nodules in chest images is an important diagnostic complication. Regular project radiography is a simple, inexpensive, and widely used clinical examination [2]. Unfortunately, the diagnosis of lung cancer at an early stage is limited by many technical and observational factors. In recent years, several authors have reported measurement methods for detecting changes in node size, and most studies have been limited to solid lung nodes [3,4]. A node is usually separated from the background structure until its structure is calculated. Different methods are considered to estimate the size of the allotted nodes. The simplest and most commonly used procedure is direct counting of voxels, but some methods have been suggested as a solution to the partial effect. In general, such methods are based on weighing each voxel according to the CT density value [5-7].

Lung nodules

In this study, we focus on estimating node size with a space-size approach that avoids pre-partitioning processes and requires minimal user interaction and is highly reproducible. To use the characteristic scale in place of the Laplacian computed scale [8,9]. CT images show clear bladder-shaped lung nodules that are clearer than the background of the surrounding lungs [10]. Assessing the size of small nodules and their growth during lung cancer screening is important for making a decision and planning follow-up such as follow-up diagnostic tests or biopsy [11]. In the early stages of their development, the lung nodes are approximately spherical. Most of them are seen as isolated structures. Although the relationship between nodes and blood vessels is often observed, the correlation is very small compared to node size [12,13]. They make up 25% of the solid lung nodules found in the clinical data from the ELCAP screening test. Anisotropic growth adjacent to the pleural surface can be seen in the jaxa-pleural nodes. In addition, different textual patterns of their structure can be found in the lung nodes [14].

Characteristic of lung nodule

A nodule is a generally localized material that produces a bubble shape that is lighter or more pronounced than the surrounding structures. According to these observations, a simple technique to achieve greater sensitivity when detecting a node is to carefully search the image for gray level blasters [15]. Since nodules below 5 mm are usually not detected, it is advisable to look for gray blisters from the rough surface. On the other hand, the actual size of the nodes is not known, however our search can be controlled at predetermined intervals [16]. Since we are interested in early diagnosis, 20 mm is a reasonable top size. Therefore, we need to identify gray bubbles in observations of different sizes from 5 mm to 20 mm [17]. The idea is that the selected node locations within the CT scan will be automatically placed on another time-consuming scan using a combination of CAD and manual screening techniques. The radiologist adjusts the areas around the node and the area associated with the second scan for subsequent quantitative analysis, such as the first scan or relative size of the nodule volume for screening [18].

CT images of lung nodules

Figure 1 gives the sample images for lung nodules disease prediction and classification. Lung cancer screening using helical CT imaging consists of two stages, the screening procedure and the detailed screening method. First, the screening framework detects abnormal sites larger than 5 mm from 3D images of the lung using a small CT [19]. The most dubious areas are the comparison of serial CT movies. Second, the comprehensive sampling method uses images close to the Region of Interest (ROI) through High Resolution CT (HRCT) images [20]. This method classifies cancer. The accuracy of the diagnosis is increased by analyzing the difference between the front and back images by injecting different materials. Comprehensive screening mode sample rate is 5.0 percent and comprehensive sample mode biopsy rate is 0.5 percent [21]. As mentioned above, a comparative reading between a series of events is important for early detection of lung cancer testing. However, this system loads to receive movies, so a nonmovie system needs to be set up in a diagnostic environment [22]. Morphological imaging, commonly called Computed Tomography (CT), is a common method of radiology used to detect and localize abnormalities and tumors. CT is the main imaging technique used to determine lung nodules and is now used as an important diagnostic tool for lung cancer screening [23]. The growth of nodules seen on CT scans taken at different times is an important feature of the malignant pathological nature of small lung nodules. Typically, volume measurements are performed to calculate volume using digital calligraphy or a computer algorithm [24]. Digital vessels do not allow optimal use of existing data as linear dimensions only allow defining average and maximum diameters [25].

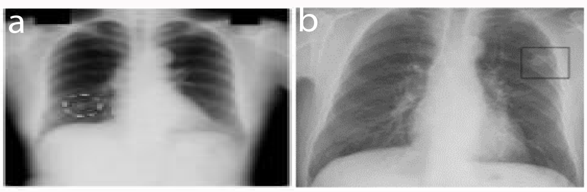

Figure 1: Lung nodules image a and b sample images.

Related Works

Han et al. [26] presented the most common databases of lung CT imaging include LISS, 271 computed tomography, and 677 abnormalities. CT image signs of lung disease of the 677 CT images commonly seen in imaging are divided into nine types of symptoms. This is an important fact of the CISL regions. Additionally, in order to generalize the database, all private CT-scan data was deleted or replaced with the given values. An important feature of our LIS database is that have developed a perspective on the symptoms of CT images of lung disease instead of lung nodes. It therefore provides computer-assisted use for diagnostic, diagnostic research, and medical education.

Nizami et al. [27] has studied Computer-assisted detection of lung nodes provides the most accurate method of locating nodules, leading to a reliable diagnosis of lung cancer. Lung division is the first step in the process of automatically detecting nodules. In this paper, we present a bandwidth-based approach to effective lung compression. The specific method selects the optimal driver image for the frames of the driver width pockets. The frames are applied to the cluster of coefficients using k-means or cluster, resulting in a fragmented area of the lung. The algorithm tested 350 local images of 5 local patients and a total of 71 images from a database commonly available on a CT scan database.

Farag et al. [28] proposed Use indirect locations as a signed remote function. The intensity of the image is combined with the structural statistics of the various sections of the shape model. Matching criteria are used to solve the process of correcting the indirect representation of the shape model and image. The transition parameters are created by improving the slope descent to fix the shape correction process, thus marking the boundaries of the "head" node. The setup process takes into account image intensity and previous format information. The comparative density estimation approach is used to control the statistics of node and background regions.

Zhang et al. [29] proposes node development filter for automatic node detection based on CT behavior and shape behavior. First, the brightness of the image is improved by calculating the difference in CT value between the inner square and the outer empty square. A uniform action is defined to avoid the boundary area and the local response at the filter angle. Finally, the specific filter separation is a combination of the CT value variance function, the line control function, and the homogeneous function, which can increase areas like this node and prevent line and edge and corner area responses. Additionally, it uses integrated imaging technology to speed up filter processing.

Fazli et al. [30] have studied automated methods in clinical practice provide rapid and accurate analysis of scanned images for diagnosis. According to these methods, the clinical picture department plays an important role in the process of separating cells from healthy organs. By creating an accurate category, drugs can identify and classify the indistinguishable locations of the scanned images and search the database for similar events. In this study, we suggested an effective and appropriate method for extracting lung CT images. The proposed algorithm uses adaptation average conversion method, which evaluates the throughput parameter using standard speed estimation. Because the kernel density calculation method is closely related to the conductivity parameter, a particle mass optimization algorithm is used to improve this parameter.

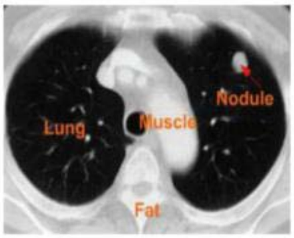

Figure 2: Lung CT scan image.

Tariq et al. [31] have studied that automatic detection of lung cancer using Computer Aided Diagnosis (CAD) is an important part of clinical applications. Manual detection of a node can be time consuming and expensive because computer systems can be used for this purpose. Figure 2 shows the CT scan image with lung nodule. The automated system has two phases, namely the division and expansion of the lung, and the extraction and classification of traits. The separation process separates the lung tissue from the rest of the image, and only the examined lung tissue can be considered as a candidate site for the detection of malignant nodules in the lung area. The view vector is calculated for abnormal sites, and regions are classified using the neuro dimmer classifier.

Diciotti et al. [32] solve the vessel attachment problem by suggesting an automatic correction method for the initial estimated section of the lung node. This method is based on the analysis of the local shape of the initial section for the use of 3-D geodetic distance map representations. The edit method cleans the node section internally using authorized shipping attachments without changing the node boundary elsewhere. The method was tested using a simple initial approximation section obtained using a standard image limit. The full segment algorithm examined the small lung nodes found in the ITALUNG screening test and the smaller nodes in the Lung Image Database Consortium (LIDC) database.

Guanglei et al. [33] presented CT for evaluating the following images. The innovations of this algorithm are twofold. Fuzzy algorithm obtains the node surface using a three-dimensional radiation casting method that is new and efficient. Figure 3 shows the working function of lung nodule prediction. Then use the 3D distance conversion method to improve the reconstruction of the partition method and to manually mark the impact of the seed point. Guo et al. [34] proposed vector image traits to improve lung cancer diagnosis, level, use training Support Vector Machine (SVM) including diversity and CT system characteristics from pedestrians. From the other image factors including SUV and CT texture were extracted from PET/CT images.

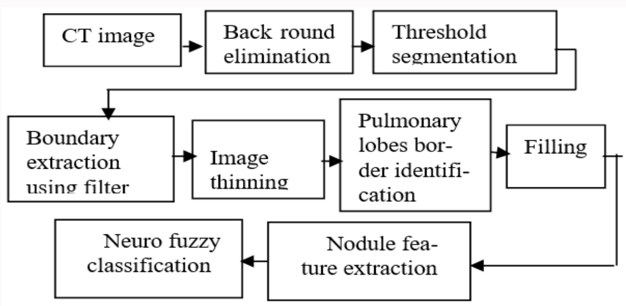

Figure 3: Flow diagram of proposed system.

Yiming et al. [35] have studied lung disease often occurs in the nodes. Lung nodule is one of the major symptoms of pneumonia. The characteristics of the lung nodes always indicate the nature of the lung disease. The detection of lung nodes is very important in the diagnosis of lung cancer. The study of lung nodes is now the subject of research. CT is a new type of medical im-aging device with high resolution and sufficient image information. But radiologists need to read a lot of pictures to identify small nodules in the lungs. This can easily lead to misdiagnosis and misdiagnosis. This paper EM method is used to locate and divide lung nodes in CT images. The application shows that this research method is the most effective method using early detection of lung cancer nodes and computerized analysis of lung nodes.

Detection and Classification of Lung Nodules

Data collection and pre processing

Images are collected from the Lung Image Database Consortium (LIDC). Spiral CT scan images are available at 120 kV. The diameter of the data collection was 500 mm, the reconstructed diameter was 380 mm, and 0.75 l was 25 mm. Strip thickness 2.5 mm. The image is stored in DICOM format [36], which omits patient description; on the other hand, it protects other information such as the reconfiguration parameter and the volume value and includes the scanner model used in each case. The XML file contains information about the lesion, which was reported by four radiologists. Show a wide dynamic range of image intensities. Often, the quality of a film is influenced by a variety of objects, including variations, attractive intensity, sound, jumps, and movements. Therefore, the purpose of image pre-processing is to remove any unwanted data from the images without affecting the useful details. The basic solution to this type of problem when processing an image is to change the image intensity values. This is done by setting the pixel intensity values of the image, i.e., the 1% intensity values are saturated with low and high intensities. Figure 4 illustrates the fundamental blocks of detection and classification of lung nod-ules.

Median filtering: An intermediate filter is used to soften the boundaries of the lungs. It aligns the defined pixels in the image area to the core and converts the value to the center pixel. Therefore, it is better to remove the sound without significantly reducing the quality of the film. In this work, filtering is done in terms of 5 to 5 neighboring pixels.

Selection of region of interest (ROI): The image contains areas of unwanted data that do not facilitate the diagnostic process. So, it is processed and further processed only in the area of interest, i.e., the

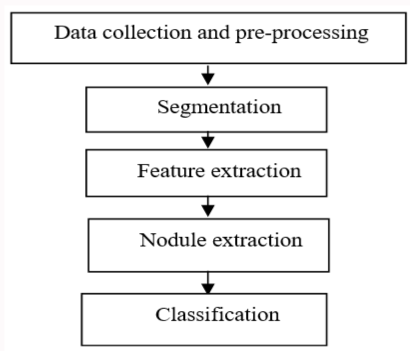

Figure 4: Working flow of CAD system.

lung area, which reduces the project length by avoiding unnecessary information. Cultivation is an individually designed method where the user selects an area using the GUI tool.

Contrast limited adaptive histogram equalization: The histogram equation is widely used to increase the variability of images in many applications due to its simple operation and functionality. It has been found that a defect in a histogram equation can change the brightness of an image after a histogram equation, which is mainly due to the flat properties of the histogram equation. Adaptive Histogram Equalization (AHE) method especially useful if the background and foreground are dark and marked with short gray meanings [37]. However, due to the limited variation of the lung images, many details need to be included, so it cannot be easily presented to doctors. This can lead to late diagnosis and poor behavior. In many such cases the histogram equation plays an important role, although local changes remain unnoticed. They have adopted the Contrast Limited Adaptive Histogram Equalization (CLAHE) technique to enhance the CT image. CLAHE [38] extension calculation is a modification of the AHE that changes the user-defined maximum, e.g., the height of the local histogram internally at the clip level, thus increasing the maximum variability coefficient. This reduces the size of the most attractive areas of the image, prevents sound accumulation and reduces the shadow effect at the edge of the AHE. CLAHE settings are the pixel environment size and the location of the histogram clip. The algorithm of CLAHE [39], is as follows:

Obtain all the inputs.

Pre-process the inputs.

Process each contextual region (tile) thus producing gray level mappings.

Interpolate gray level mappings in order to assemble final CLAHE image [40].

Segmentation

Separation is used at the base of the entrance. Threshold technique separates images by creating binary partitions according to the intensity of the image. Areas associated with the lung area were identified and the lungs were not considered. Created a binary image with gate value; that is, all pixels that exceed the gray limit are equal to 1, and the remaining pixels are equal to O.

$$g(x,y)=\begin{cases}1 & f \quad f(x,y)>T \\ 0 & f \quad f(x,y)\le T\end{cases} \quad (1)$$

It is calculated by equation 1, where T is the initial value and f (x, y) is the input image. The fill function determines which pixel holes, which automatically changes the value of the detected pixels from 0 to 1 and fills the holes in this binary image. The edge of the binary image is fixed and the lung zone is obtained by reducing the filled image.

Nodule detection

Many nodes around the lungs or in the blood vessels are ignored by many of the techniques mentioned above. New technologies have been developed to identify nodes in these areas. First the boundary of the binary image is calculated by the transformation functions. The border draws the original image and separates the area of interest. In this way, the gray matter near the lung wall in the newly formed image resembles the inner lung and also helps to identify nodules near the lung wall. Nodes are named using associated components.

Feature extraction

Various signs form the basis of taxonomy [41]. Geometric features similar to area, diameter, circumference, and irregular index were determined from identified lung nodes. The following parameters are extracted from the identified nodes.

Area: It is calculated by summing the pixels in the area of interest along with the value from the binary image. This measurement value returns the number of actual pixels in the area of the detected object.

Perimeter: This is the total number of pixels outside the detected area. It is calculated by measuring the distance between each pair of pixels connected in a given area.

Mean: The mean is distinct as the rundown of the pixel standards divided by the total number of pixels that lie in the definite area as shown in equation 2, where, p (i, j) is the concentration value of the pixel at the point (i, j) and M x N is the size of the picture.

$$\mu=\frac{1}{mn}\sum_{i=1}^{m}\sum_{j=1}^{n}p(i,j) \quad (2)$$

Equivalent Circle Diameter: It is the diameter of the circle, which would equivalent area of that object. It is given by equation 3.

$$ED=\sqrt{\frac{4\,Area}{\pi}} \quad (3)$$

Centroid: It specify the middle mass of the detect region.

Irregularity Index: Depending on the shape of the tumor, the cancerous nodes may be circular in shape. To detect abnormalities, it measures equation 4, where P is the circumference and A is the area [39].

$$I=\frac{4\pi\,Area}{P^2} \quad (4)$$

Eccentricity: The circular evaluation of the object is strange. It is the ratio of the distance between the sprint and the distance cantered along the half-large axis of the object. The value ranges from 0 to 1, where 0 is a circle and 1 is a straight line [42].

Classification

Neural networks, a mathematical model developed to mimic the functions of the human brain, are called Artificial Neural Networks (ANNs). It consists of several simple units called neurons that communicate with each other through heavier connections. ANN is a nonlinear classifier, which is why they are the best candidate for classification when the data relationship is unknown. Another common feature is their ability to adapt and learn [43].

They are able to interact with data between data and related target vectors. The distribution network is used for classification purposes as shown in Figure 6. It consists of three layers, an entrance, a concealed and an output layer [44]. Hidden layer size 10 selected. It uses the tan sigmoid transfer function on the hidden and output layers as shown in Figure 7. This is a supervised classifier. Networks generate 70% of the data and the associated target vector. This will be verified with 15% input data. A trained network is now used to classify tumors as cancerous or noncancerous [45].

Review Methodologies

We planned and reviewed according to recommended procedures. There are six basic levels in this configuration. First, it raises existing research questions based on what needs to be done for ongoing research. Second, it explains the search strategy to demonstrate how

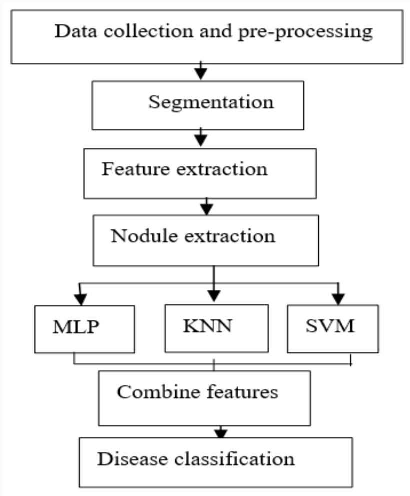

Figure 5: Working function of CLAHE algorithm [40].

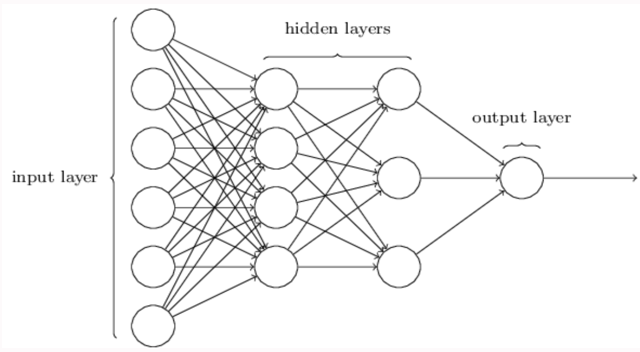

Figure 6: Structure of feed forward neural network.

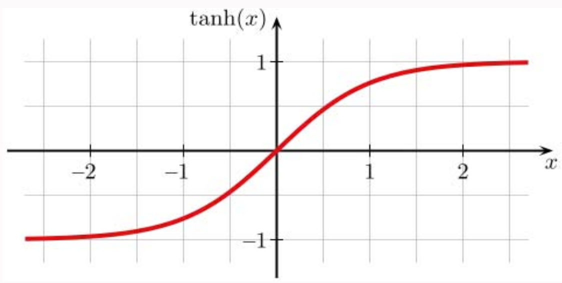

Figure 7: Tan sigmoid function for hidden layer in neural network.

related studies are defined. Search terms and resources are defined in this space. Third, it includes revised research test criteria that are not used to answer research questions. Fourth, the selected studies will be further revised based on the quality characteristics. Finally, the required information is obtained from the selected studies and analyzed according to the research questions. Details of each step are given in the following sections.

Research questions

The purpose of this study is to analyze studies focusing on placing lung nodes in CT images based on hybrid deep learning techniques of software project evaluation. Review methodology for review questions stimulates the review process. The main purpose of the review is to answer the following research question:

RQ1: Which sources and types of data had been used?

RQ2: How did lung nodule diagnosis improve in prior studies?

RQ3: How is the accuracy of ML/AI/DL-based models recommended in prior studies calculated?

RQ4: Is SVM able to significantly improve accuracy in comparison to standard baseline techniques?

RQ5: How were the specific models evaluated compared to the other models in previous studies?

Search strategy

The content of the search strategy is to find research that will help RQ respond. The three levels of search strategy include identifying keywords, defining search strings, selecting data sources, and finally locating data sources.

Identifying keywords and defining search strings

- We used the following terms to derive search terms:
- Identify keywords that match the questions listed above.
- Find all synonyms and misspellings of the word.
- Use a Boolean operator to get a record of any (or all) terms OR to match similar terms.
- The Boolean operator should use AND to combine keywords and record any log containing all terms

The entire set of search terms was prepared as follows: (analogy OR "analogy-based reasoning" OR "case-based reasoning" OR CBR) AND (software OR system OR application OR product OR project OR development OR Web) AND (effort OR cost OR resource) AND (estimate* OR predict* OR assess*).

Selected data sources: The database contains 7 electronic databases for preliminary research (Springer Link, IEEE Xplore, ACM Digital Library, Elsevier Science Direct, CiteSeer, InderScience, and Google Scholar). Since they are fully covered by selected data sources, some other important sources such as DBLP, Cite Seer and Computer Science Bibliographies are not considered. Search terms in 8 databases before searching for journal and conference documents. This is because different data-base search engines use different search strings to sort different databases. Search the top five databases of titles, biodata and keywords Google Scholar offers a full search of texts with a title and millions of inappropriate entries they have limited search from 2000 to 2020.

Search process

Search phase 1: Search eight databases separately, then collect returned documents from CiteSeer and create a set of candidate papers.

Search phase 2: Scan the relevant paper reference lists to find the most relevant paper If so, add them to the package.

Selection criteria

The systematic search time of the review is not ideal as the review may be biased in selecting relevant studies. At this stage, the content of the paper, the abstract, and the conclusion of the conference should be evaluated to select the objectives of the current research. The inclusion and exclusion criteria are defined as follows,

Table 1: Quality Assessment (QA) for review.

No.	Question
QA1	Does the proposed method lead to improvement of performance in?
QA2	Is the specific evaluation method compared to other methods?
QA3	Are survey results available to support the findings of the paper?
QA4	Are the objectives of the study clearly defined?
QA5	Is this research improving the educational or professional community?
QA6	Is evaluation accuracy measured and reported?

Inclusion:

- Lung nodule diagnosis considered being the main model of evaluation.
- In the case of duplicate documents, the newest and most complete sheet is selected.
- Lung nodule diagnosis improves the performance (not only using as a complementary model).

Exclusion:

- Duplicate publications of the same study (there are several publications of the same study, only the most comprehensive in the review).
- Evaluation of effort metrics other than development effort such as testing and maintenance effort.
- Study topic is software project control.

This study evaluates software development efforts and focuses only on studies that have worked to improve lung nodule diagnosis. Therefore, the aims and objectives of each paper are carefully considered according to the selection criteria, which will lead to a review of the selected studies (Table 1).

Quality assessment

A selected study in Quality Assessment (QA) is first used to identify data obtained in meta-analysis, which is an important data collection strategy. Although, the data found in this review are made in different test formats, and meta-analysis is not used if the amount of data is relatively small. For this reason, quality assessment results are not used to obtain quality. Instead, we used it to interpret the review results and to demonstrate the strength of the assumptions. In addition, the results of the quality assessment are given as an additional criterion for the examination. Table 1 gives the quality assessment questions for paper selection process. The quality of the relevant papers was evaluated based on the 6 questions presented in the table. Possible answers to this question are as follows: We have divided the quality assessment questions to evaluate the intensity, reliability and relevance of the relevant studies. These questions are listed in Table 1 and are derived from some of them (e.g., QA2 to QA5). There are only three answers to each question: "Yes", “Partly" or "No". All three answers were rated as follows: "Yes" =1, "Partly" =0.5, "No" =0. For this study, its rating was calculated instead of QA. Some previous studies have used lung nodule diagnosis as an additional technology to provide a larger model. These types of studies do not help to answer the research questions of the current study. Therefore, in the first phase of quality assessment, we identified the main objectives for improving lung nodule diagnosis.

Data extraction

At this stage, data were collected for research questions and activities before selecting relevant questions. Each study is carefully analyzed to reach conclusions and to obtain useful data to answer previous research questions.

Data synthesis

The purpose of the database is to gather evidence from selected studies to answer research questions. Once the data collection is complete, the analysis and review process will be simplified and the results will be expanded. At this stage, the selected files are compiled and integrated, which simplifies the comparison process between different types of papers. The data collected are briefly listed based on the key factors used to address research questions. Data synthesis is an important part of systematic review, as strong evidence and conclusions can be drawn as a result of accurate analysis of data collected from previous studies.

Selected papers

Selected papers conquered the title: Engineering (323 papers). Segregating lung nodule diagnose concept and consistency allows to focus on production issues and develop new engineering solutions to achieve sustainable production has the number of files integrated are 180 papers. Selecting the criteria will decrease files to 88 papers. Finally, the quality assessment of the leftover papers gives a total of 26 papers. Thus, the remaining topics are very limited in terms of papers and cover many levels. Figure 8 shows the overview of paper selection process.

State-of-Art Techniques for Lung Nodule Detection

Ozekes et al. [46] have proposed a Computer Aided Detection (CAD) system was introduced based on the acquisition of a 3D feature to detect nodules in the lungs. First, eight-way searches were used to identify Regions of Interests (ROI). Then, turn on the 3D attachment component labelling, integrity calculation, thickness calculation, definition of medium pieces, calculation of vertical and horizontal widths, regular calculation and calculation of vertical and horizontal black pixel coefficients. For each ROI, Neural Network (NN), Support Vector Machines (SVM), Naïve Bayes (NB) and Logistic Regression (LR) methods were used. These methods were practiced and tested through K-cross checking and comparative results were obtained. Zheng et al. [47] have proposed to increase CAD sensitivity when detecting solid breast mass, it has been proven that the optimal training base should contain a high percentage of heavy but solid mass. Although creating a large image database has always been an important research objective and endeavor for cat development, the study reveals that the use of a large study database dominated by a relatively simple population is not very useful in achieving this goal and requires more effort for identification. Huang et al. [48] have presented MLP neural networks and SVM models are simple and compatible with hardware design. With the expansion of

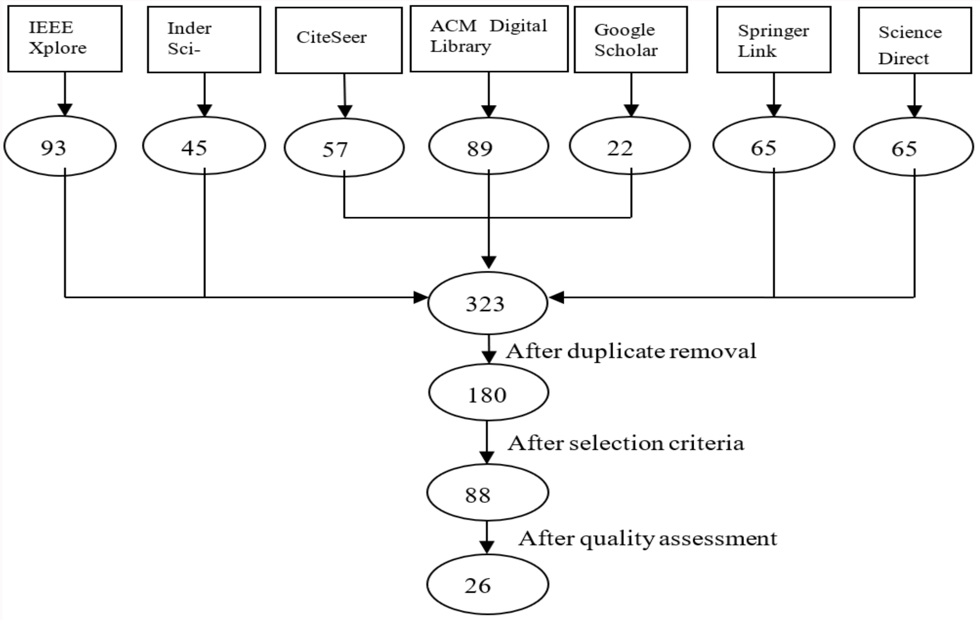

Figure 8: Process of paper selection.

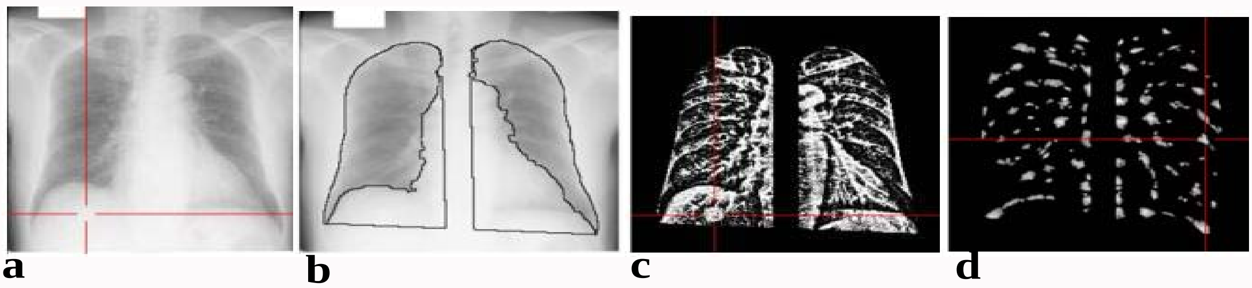

Figure 9: Original image containing a subtle nodule in the (a) Hidden areas (b) Lung image area (c) Enhanced image (d) Region's image containing an extremely subtle nodule.

the database, features removed from new events are easily created and used as a reference. If the performance of the classifier is not adequate for the ultrasound image, the off-line training algorithm can be used to obtain new weighting components by changing the settings genetic settings or adding several specialized training models to the training package. It is noteworthy that the classification modules can change the weight components without changing other functions.

Kakar et al. [49] have proposed the thorax CT provides a mechanism for dividing and identifying ulcers and lungs based entirely on automation. For the partition area, we extract system features by filtering the caper images and then merging these features to allow target size using the Fuzzy C Means (FCM) cluster. Because clustering is sensitive to the onset of cluster prototypes, the optimal organization of cluster prototypes is completed using a genetic algorithm. For the authentication level, in addition to the formatting attributes, we used cortex as a mechanism for obtaining statistical attributes. Finally, the Support vector machine (simple SVM) was subjected to integrated and standardized data training and testing. Wolf et al. [50] have proposed the lung section is used to speed up the processing time and to remove the bad false positives that appear outside the lungs, limiting the analysis to a Volume of Interest (VOI) at the primary level. Lung partitioning is made possible by the use of imaging operators to improve partition accuracy by first entering the Hans field subdivisions of the constituency. Format based properties are used at this stage to create a list of candidates. When calculating properties each candidate is considered the most complex and computational qualities.

These features are based on the described pixel intensity figures, 2D and 3D format descriptions, and the location of the corresponding structure. Campadelli et al. [51] have proposed a computer system designed to detect lung nodes. It uses two different multilevel schemes to identify the respiratory tract and to separate candidate sets at high sensitivity speeds. At the heart of this work is the classification of components into the most unbalanced candidates, using Support Vector Machines (SVMs). Figure 9 shows several experiments with different cores and different training boxes. The results showed that cost sensitive SVMs trained on highly unbalanced data sets were achieving reliable results based on sensitivity and personality. Lee et al. [52] have presented random forest classification facilitates clustering method for locating lung nodes. In advanced mode, all data is collected by combining the node and non-node events of the training package. It will study the similarities between node and non-node features. Each cluster is divided into two groups: Node and node events. The training package forms several groups using the original label of the events. The training is conducted using a random forest classifier. In the experimental phase, the events of the test set are presented in an advanced classifier and then categorized. Several experiments were performed using the proposed method and other existing methods. Zhao et al. [53] have proposed approach to machine learning approach to reduce false positive lung nodes detected by CAD algorithms in multi-piece CT scanners. Depending on the estimated nature of the thin-section scans, a genetic algorithm is used to determine the optimal nature of the class fire preparation, which eliminates as many false positives as possible while maintaining the original nodes. Out of the 15 characteristics calculated for each node, our approach selected 9 as the optimal characteristic as a subgroup size, resulting in a classification of 9 classified features with 98.5% sensitivity and 82.9% specificity with single leave evaluation. Boroczkya et al. [54] have proposed a subgroup sampling method based on a genetic algorithm to improve the efficiency of a false positive CT scan of the lung node. It is connected to a classifier based on auxiliary vector machines. The specific approach automatically determines the optimal size of the feature set and selects the most suitable feature set. Its effectiveness was tested using a pulmonary node database obtained by multiline tomography. For each structure identified from the 23 identified characteristics, the recommended method determined the sub-group size of ten optimal features and selected the ten most suitable features. Dodd et al. [55] have proposed Lung and lung cancer in malignant tumors in the United States. Five-year survival is low, but treatment of early-stage disease significantly improves survival chances. Advances in multi-detector sequence computed tomography technology provide small lung nodules and detection and effective screening equipment. Farag et al. [56] have presented an approach to modelling lung nodes using our data using the original node structure and shape characteristics to create an average sample template for the node type. The ELCAP Low Dose CT (LDCT) scan database is used to compile the latest statistics for the models. These models are ideal for locating nodes in a variety of approaches to machine learning, including biosynthetic methods, SVM, and neural networks, and can be used to increase calculations using genetic algorithms and ad stimuli. An important development of the new node models is the study of parameter models that show significant improvements in sensitivity and uniqueness. Kouzani et al. [57] have presented It detects nodules in the lungs by classifying them into nodular and non-nodular types. It is based on random forests and is a group of explorers who enjoy the trees. Each tree generates a taxonomic result and the combined result is calculated. Three tests are performed on the lungs of 32 patients, including thousands of images taken by expert radiologists at node sites. Introduces and discusses classification errors and execution times.

The lowest classification error (2.4%) occurred using the advanced method. Campadelli et al. [58] have presented rear anterior chest radiographs provide an automated lung node detection system. The system separates the candidate area using three different and continuous multilevel radiography programs. Demonstrates the effectiveness of our multilevel structure compared to the results presented in the literature. Training systems that use a variety of features for candidate classification have been tested, SVMs can be used successfully for this task. Dehmeshki et al. [59] have proposed Effective classification of CT lung node using model and auxiliary vector machine. The main advantage of the model is that it reduces the amount of data when storing all valuable discreet information. This is very important for vector machine training. Because it controls the amount of training data, it is relatively fast to train and classify vector machines. Lung node classification test results show good detection speed and satisfactory detection rate. Siddique et al. [60] have proposed a multi-force Genetic Algorithm (GA) uses a broad island model that collaborates with a species block to identify lung nodes in chest CT images.

The genetic algorithm is a machine learning model that derives its nature from the evolutionary processes of nature. There are two stages in the detection process. In the first step, a CA-based template was used to effectively determine the target position in the observed image and to select an adequate template image from multiple reference formats for quick template configuration. Heeneman et al. [61] have proposed a gate system that can localize as many nodes as possible while reducing the number of false positives. A quintal approach is used in the feed sections to localize the nodes in the 3D scan area and to reconstruct the two-dimensional fragments. Next, the sliding window pattern on the plot is used to obtain the node coordinates (x, y). A two-dimensional conversion neural network is used to classify these windows. The advanced wind system can detect and localize an average of 2.1 (1.5%) false positives on average at 60.1% of all nodes. Samala et al. [62] have proposed a Computer Aided Diagnosis (CAD) Computed tomography of the chest plays an important role in the early detection of cancer and in the detection of lung nodes, thereby significantly reducing mortality. The most important step of the CAT system is the final classification module is shown in Figure 10, which separates the malignant lesions using their internal imaging features.

Antonelli et al. [63] have proposed decision support system for determining key features of lung node detection using machine learning techniques based on eye monitoring. This method first analyzes the methods scanned by expert radiologists during routine examination. Key features are used to highlight key areas related to the diagnosis, as well as the possibility of estimating the weight of visual features learned from various experts. The structure was evaluated using CT lung node test data, and the results showed the clinical significance of the specific technique, which could be generalized to other diagnostic programs. Retico et al. [64] have proposed a fully automated method has been developed for the detection of

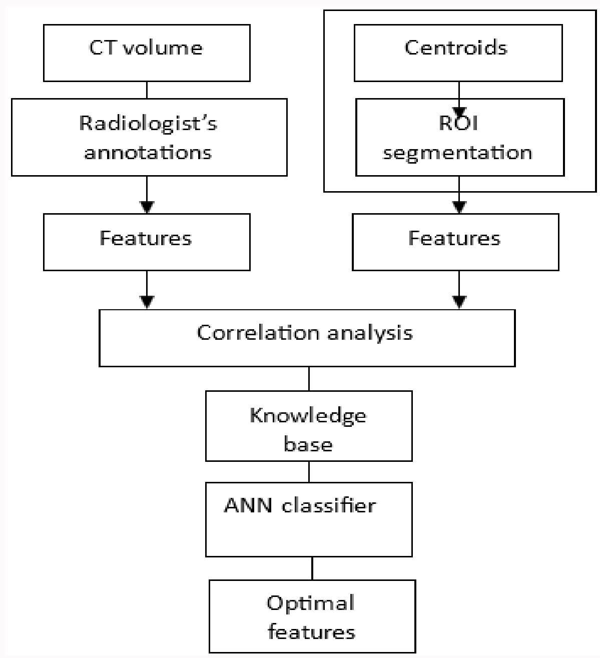

Figure 10: Identification process flow with CT computed topographic ROI region of interest extraction.

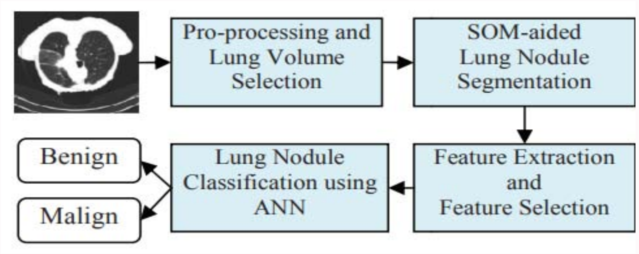

Figure 11: Architecture of the designed CAD system to detect and classify pulmonary nodules.

pleural nodes in the small lung and Computed Tomography (CT). The directional gradient concentration method is applied to the flora and creates a list of candidate nodes based on the image. Each candidate node has 12 forms and text features that analyze rule-based filtration and neurological classification. This detection system was created and tested in a database of 42 small CT scans. The K-Times cross-examination was used to evaluate the effectiveness of the neurological classifier. Iwano et al. [65] have proposed measurements of lung tumor size and size can be useful in determining the status of chemotherapy or radiation therapy. Further CT imaging is needed to determine if the lung node has grown and how fast it has grown. Lung node doubling time is one of the signs that distinguish malignant nodes from empty nodes. Node awareness, node detection and measurement can be done completely automatically. In addition, we must program the CAD program to determine the normal structure of the blood vessels, trachea, and pleura in the chest. Suiyuan et al. [66] proposed a CAD system for detect autoimmune nodes in the lungs on a serial CT scan based on shape features. To restore the original 3D shape of the nodes, the serial CT images are cut into equal sizes of X, Y, and Z. Second, treatment is given before isolating the lung parenchyma. Third, identify Regions of Interest (ROIs) as potential nodes through gray matter and local growth gateways. Dandil et al. [67] have studied lung cancer is the most common of the various life-threatening tumors. Nodules forming in the lungs, such as circular or spiral complicate their diagnosis. Early diagnosis can help identify treatment steps and increase treatment success rates. CAD system was created using CT images to confirm the early detection of lung cancer and to distinguish between malignant tumors. The CAD system is designed to provide node separation in the lobes using a SOM neural network model, and classifies between malignant and malignant nodes with the help of ANN. Novo et al. [68] have studied Suggests a new approach to identifying a lung node candidate. Figure 11 shows a 3D intermediate hessian-based filter to identify circular structures that can be identified as nodes. This technique has proven its accuracy in obtaining pulmonary vessels, provides clearer candidates than other approaches, responds less in the presence of acoustic material, and provides better continuity in vessels that cause false positives. In this respect, they are very different from the nodes of the posterior analysis.

Zhai et al. [69] have proposed CAD systems to detect nodules in the lungs are suggested in X-ray CT images of the lungs. Local development and rule-based methodology were used to identify node candidates. Classified and updated K-I for the Max Neural Network with Fuzzy Min-max Neural Network Classifier with Compensatory Neurons (FMCN). A cluster looks like a hyper box, so the K- or clustering algorithm is implemented to determine the extension coefficient (hyper box size). Ng et al. have proposed Content-based image recovery strategies are becoming more important, helping clinics to diagnose and monitor. A description of the specific features of the domain is shown before reconstructing the tumors in the lung which shows in Figure 12. This work offers a way to improve the cyclic variability of hierarchical spatial interpretation and to provide filter node for replacing images with a new binary interpretation.

Agarwal et al. [70] have studied Lung cancer is being studied as a major cancer, indicating that more than one million people die each year. This creates the need for early detection of lung nodes in computed tomography clinical images. There are different methods and techniques, but none of them provide the best detection accuracy. The various stages of the proposed CAT system are described. Isolation of lung area from chest CT images, isolation of lung area, isolation from an isolated site, classification of lung cancer or cancer. Kumar et al. [71] proposed develop a two-stage CAD system that can automatically detect histological images, such as a CT scan of the lungs, using a cancer node or an unwanted node. The first step involves pre-processing the input image and isolating the cancer node area, while the second step involves locating the node based on the blurred structure and the node area. The goal of the proposed work

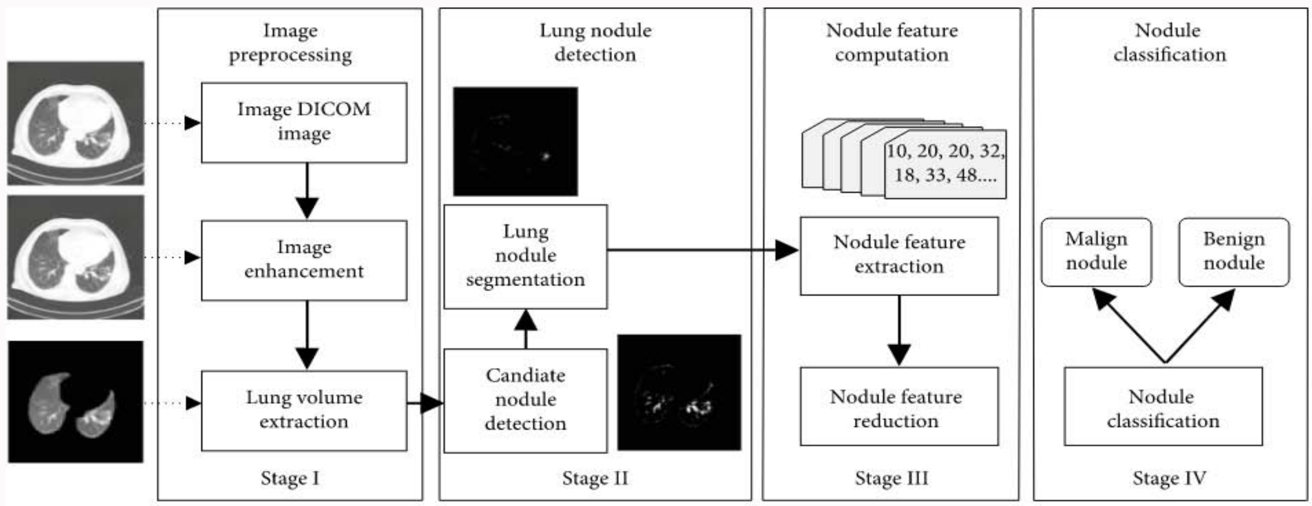

Figure 12: Illustration of different modules of the CAD system.

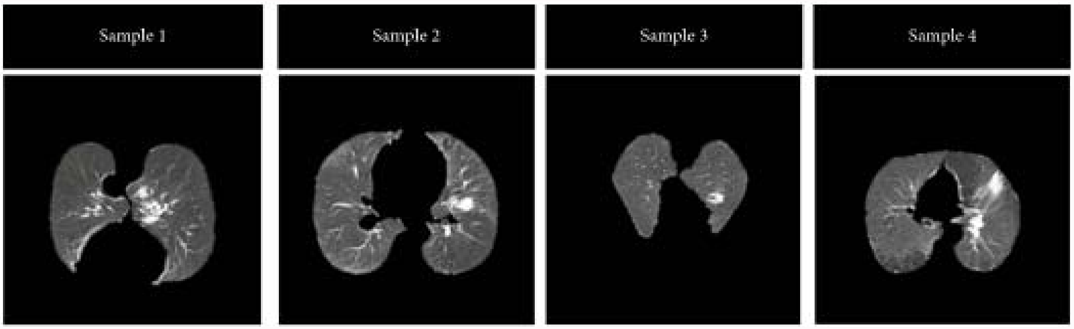

Figure 13: Comparison of automated and radiologist segmentation.

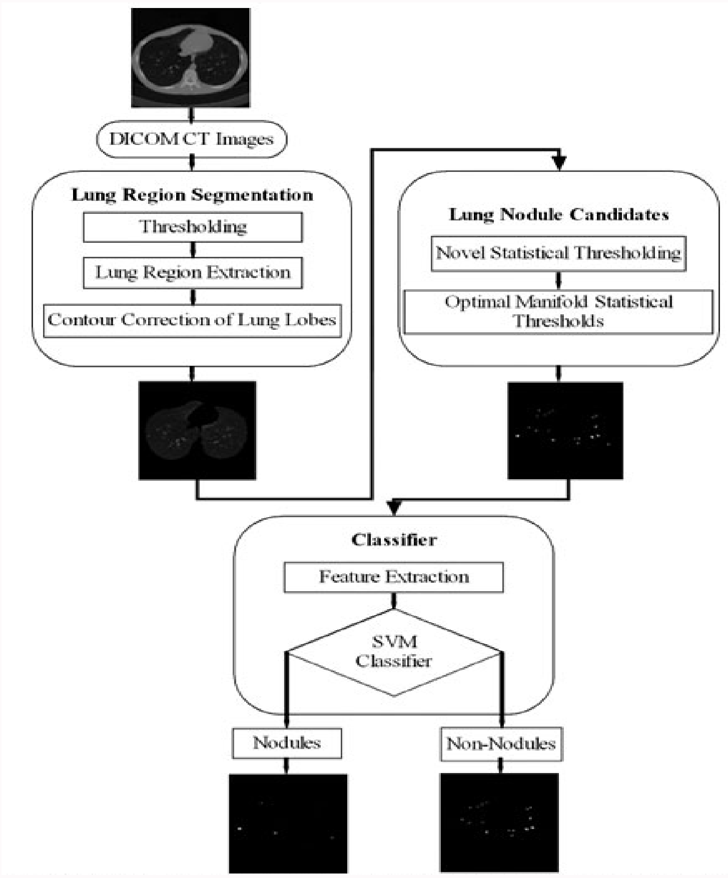

Figure 14: Workflow for preparing data for classification.

is to reduce false positive classification and maintain a high positive diagnosis. Nagata et al. [72] proposed the first parts of the chest image divide the lungs using the active shape model. The program identifies early node candidates using a method previously described by teachers. The proposed scheme classifies node candidates into nodes and false positives using the two-level classification method suggested in this study. To evaluate the performance of the specific node detection program as Figure 13, we conducted experiments with 125 nodes in the JSRT database. Thomas et al. [73] Morphological functions are used to pre-process the images, while gray level coagulation matrix is used for the feature extraction process, as well as SVM, minimum distance, and K-near classifier. The test analyzes a set of data to evaluate the performance of different classifiers. The performance of SVM classifiers is considered to be the best classifier based on right and wrong.

Han et al. [74] CT images of 2D and 3D system features were evaluated to detect lung nodes using a large database LIDC-IDRI. The 905 nodes (422 malignant and 483 malignant) from the database created based on the radiologists' imaging range are lethal to some professional observers. In Figure 14, more directions were added to the relationship with more neighboring vowels. A well-established SVM classifier was used based on the features of the 2D and 3D hurricane system. About half of the benign and malignant nodes were trained and the left half of the nodes was examined. Tartar et al. [75] proposed a CAD is proposed classification of lung nodes as malignant and non-malignant. The CAT system, with specific group training classifiers, provides significant support to radiologists in the diagnostic process to achieve high classification efficiency. Kumar et al. [76] have studied early detection of lung cancer can lead to a significant reduction in lung cancer mortality, which is more than

17% of cancer-related deaths. Radiologists have several cases per day to make an early diagnosis. CAD systems can make radiologists think twice and speed up the whole process. Then evaluated this method as the need for different combinations of lung node packages and isolated similar nodes from the identified database. When calculating the accuracy of this system, anonymous data sets and computer-defined malicious data are used as the basis for anonymous query nodes [77]. Ying et al. [78] proposed a new project suggests identifying individual lung nodes in CT images. ROIs are classified based on the multi-dimensional morphological filtration method; the ROI features are selected using probability allocation. Chen et al. [79] have proposed CXR, where ribs and ribs are trained through neural networks (MDANs). CAD program utilized to reduce ribbon-induced FP and isolate nodal yokes. VDE technology blocks ribbon and nerve variables in CXR while maintaining soft tissue opacity using the MTANN technique created using original dual energy imaging. Sixty morphological and gray level-based features are removed from each candidate from the original and VTE CXR. A linear support vector classifier was used to classify the node candidates. Puentes et al. [80] proposes diverse CAD systems based on multiple machine resource units that can provide semantic assessments with low accuracy as a team of experts to assist in the diagnostic process. However, large-scale production of mechanical raw materials can sometimes create unwanted noise. Therefore, we suggest filtering the bad segments using an external detection algorithm that identifies the farthest segments from the segments. Results are compared with the CAD system, which is based on explanations from expert sources and semantic assessments by radiologists.

Hadavi et al. [81] have proposed the CAD system adopted to diagnose lung cancer uses lung CT images as input and allows doctors to perform image analysis based on an algorithm. With the help of CAD, doctors can make the final decision. This article or section needs sources or references that appear in credible, third-party publications. Images contain unwanted data and some important processing features; increases pre-processing images and eliminates key features by eliminating distortion. The system was used to scan the lung CT, so several pre-processing methods were used to magnify the CT images, such as a copper filter and a growing area. After pre-treatment, the lung cancer nodule is isolated according to its merits. Smith et al. [82] proposed a CAD system based on multiple computer-derived Weak Segmentations (WSCAD) and show that its diagnostic performance is at least as good as the predictions made using the manual radiology sections. The specific CAD system separates a set of image features from the weaker sections and uses a set of classification algorithms to predict semantic values such as gravity. Parveen et al. [83] have studied Computer-aided detection systems have been developed to increase the accuracy and speed of execution. Imaging techniques such as radiography, CT and MRI are currently available in the field of medical diagnosis. The medical film section is the most important part of image analysis. Although the growing method gives the best results in a normal area, it is not an idea to select the seed points manually. Geiger et al. [84] a computer-assisted diagnostic method for classifying lung nodes by size and shape was developed without paying much attention to system features. In this paper, structural and morphological features from selected lung nodes were extracted from the LIDC dataset. Several class fires were used to identify deadly and empty lung nodes, including trees, nearby neighbors, and SVMs. Chunran et al. [85] have proposed lung node detection and separation method is based on Fully Convolution Network (FCN), stage set method, and other imaging techniques. A lung CT images were made for the FCN lung department. The lung nodes in the lung area are detected using the threshold method and other imaging methods. Finally, the detected lung nodes and their assumptions are separated using the level synthesis method and the threshold method based on changes in the coordination system. The test results show that the proposed method has 100% diagnostic accuracy and can effectively detect and isolate the lung nodes using a 0.9 segment index. Therefore, this method will give us useful tips for the clinical diagnosis of lung cancer. Paing et al. [86] have proposed the system aims to detect lung nodes from continuous CT scan images. Oats threshold and figural functions are used to separate the nodes. After separation, objects that are unlikely to become nodules are removed. Geometric, histogram, and structural features are available for the classification of extremely malignant nodes. Multilayer Perception (MLP) is used up to 95% for classification and accuracy. Wei et al. [87] have pro-posed the Content-Based Image Retrieval (CBIR) proposed a classification of lung nodes with different evaluations. Lung node database LIDC from lung CT database. Two features are calculated for each node image based on the node density. A CBIR scheme is used to find ten reference nodes that are similar to each node surveyed. The results show that the accuracy and curvature in the classification of moderately suspicious and highly suspicious (symbol 5) node cancers (symbol 4) are 0.6655 and 0.6901, respectively. When our program tried to distinguish between fatal and non-fatal cases, the ACC and AUC were 0.9231 and 0.8659, respectively. During pretreatment, multiple masks are calculated using barrier techniques and morphological functions, thus removing the background and surrounding tissue. ROI are calculated using the primary database and Hounsfield Units (HU). When a feature is obtained, several features are considered to control suspicious areas. SVM algorithm is used in the classification phase [88]. Yan et al. [89] have proposed the potential diagnostic value of system features can be examined by comparing the effectiveness of radiographic index classification with a computer-assisted system. A total of 186 biopsy confirmed controls and lung cancer were obtained at the National Lung Screening Trial (NLST). Cases are matched to various clinical parameters including age, gender, smoking status, Chronic Obstructive Pulmonary Disease (COPD), Body Mass Index (BMI), and image appearance. We compared bad/fatal subjective diagnoses with similar scores from three radiologists. Wang et al. [90] have proposed a pulmonary nodule CAD system based on SS-ELM, which achieve better simplification presentation at faster knowledge speed and higher testing correctness than ELM, SVM, PNN and MLP. The SS-ELM based pulmonary nodules CAD has been planned to solve the dilemma of doubtful class data using. Liu et al. [91] have proposed a method based on the Convolution Neural Networks (CNN) for node type classification. Nishio et al. [92] have proposed the features of the lung nodes could be achieved without nodular division, and it was useful to distinguish between malignant and empty nodules. Get the feature that connects to a novel with basic component analysis, image conversion, and merging functions. This method was compared with three other systems for obtaining node characteristics: A CT density histogram, a local binary system on three orthogonal planes, and a three-dimensional random local binary system. The feasibility of the systems and the realities of the leased land were analyzed using the character analysis of the receiver movement and the area under the curve. The LUNGx Challenge team also calculated the area under the curve of our specific method based on the actual terrain of our database. Javaid et al. [93] have proposed computer-assisted node detection is recommended for the detection and detection of complex nodes such as dwarf vascular and grouped nodes. CT of the lungs is separated from the images with intense obstruction; performs a brief analysis of the CT image histogram to select the appropriate value to give the best results for the category. A simple morphological closure is used to attach the positional nodes together in the lung text. Xie et al. [94] have proposed a lung node classification algorithm that integrates structure, shape, and depth pattern information (Fuse-GST) at the final level. This algorithm introduces a system based on the Gray Level Co-occurrence Matrix (GLCM) to detect Fourier-shaped node diversity and an in-Depth Conventional Neural Network (DCNN) that automatically identifies the characteristic node-characteristic image. In terms of fabric, using each behavior, it creates an adapted spinal neural network (PPNN) and separates the results and nodes achieved by the three class fires. Zheng et al. [95] proposed a group classification method based on the initial size to identify lung nodules with different nodular symptoms. They first classify the home Convolutional Network (CNN) and take the modules and train them to ImageNet. This pre-prepared classifier is well preserved by wrapping 10 different lung nodules to determine the tip of the lung and combining the tenth set using the synthetic immunoassay method.

Mekali et al. [96] proposed methodology, the lung parenchyma is segmented using a repetitive threshold algorithm and the lung nodes are segmented using a specific modified region growth mechanism. In vascular nodes it is difficult to separate the blood vessels from the node because the side and node intensity of the attached blood vessels are similar. Two new methods of separating the vascular node from the associated blood vessels are the nodule segmentation method and the removal of the vessel based on several characteristics. To achieve the most accurate segmentation of the nodule-vessel, clean the nodule-vessel connection region. LIDC-CT examines a specific sample of lung images. The fully automated method separates vascular nodes with less computational time and more accuracy. Huanlan et al. [97] proposed that computer-aided diagnosis plays an important role in the diagnosis of lung cancer. CNN excelled in the image processing process, and the mask in the RCNN event segment surpassed other methods. However, the target is unusually small, and the background of the images is very large, resulting in numerous negative examples, most of which are easy suggestions. Abraham et al. [98] presents early networks the CAD system was designed using AlexNet, VGG16, and newer networks based on hypotheses for resolving network deficiencies for early diagnosis of lung cancer. A comparative analysis based on performance parameters shows that CNN's configuration works well than pretrained networks. Zhai et al. [99] have studied that CAD systems have been developed to detect nodules in the lungs. However, the problem of high false positives has not yet been properly addressed. In this study, they recommend a typical neural network structure (MT-CNN) to detect malignant nodules on the chest CT scan from the hollow nodules. Yue et al. [100] proposed a method of detecting individual lung nodes. It can distinguish between pulmonary nodes and non-pulmonary nodes. In addition, this method can improve the accuracy of further classification of lung nodes. At the LIDC-IDRI Image Library they use DICOM standard chest CT series images as research objects. Han et al. [101] proposed Data Augmentation (DA) system can integrate realistic/contrast 3D images preferred by 3D Generative Advertising Networks (GAN) into additional training data. However, the 3D conditional GAN-based DA approach is not limited to the general boundary box-based 3D object detection and, unlike the strict 3D segment, allows a physician to determine disease areas at the lowest nominal value. Therefore, suggest 3D Multi-Conditional GAN (MCGAN) to create naturally occurring realistic/contrast 32 × 32 nodes in computed tomography images of the lungs to increase sensitivity when detecting a 3D object. Agnes et al. [102] have studied that spontaneous diagnosis of lung cancer has recently become the most desirable job, helping experts to diagnose cancer nodes. Automatic separation of different shapes and features from 2D nodal patches is the most difficult problem to diagnose lung cancer. This article presents an effective neural network approach to the automatic classification of lung nodes from chest CT images. The main idea of this neural network-based approach is to observe the general discrimination of 2D connections under surveillance. RNN, LSTM, and CNN activated different depth neural networks to classify 2D node connections. Specific techniques are used to diagnose and predict lung cancer in the early stages. The proposed method works in two stages: First, CT. Divide the left and right lungs to reduce shape, reduce time problems, and increase accuracy of use in the deep neural network. To test the specific method, they use Mobile Net, VGG8, and Inception-V3 Deep Neural Network models as image classifiers [103]. At the same time, a two-step forecasting method is recommended at this stage. The second phase of the TSCNN Framework is built into three 3D-CNN classification networks for false positive reductions based on the specific positive panel architecture. Furthermore, likelihood of generalizing the false positive reduction model through group research.

Comparative Analysis of State-of-Art Techniques

Performance comparison of pre-processing

The main pre-processing techniques used in lung nodules are k-means algorithm, Otsu threshold, median filtering and fuzzy clustering algorithm. K-mean is the most popular method of clustering. When providing an existing database, they analyze several ways to improve the algorithm and measure the quality of the resulting cluster. They focus on database processing methods from the beginning. Unfortunately, although this algorithm has been seriously studied, little effort has been made to analyze the impact of many such improvements, which contribute to clustering quality and computational speed. Median filtration is not an unusual method of suppressing sound with distinctive characteristics. It does not use modules in the core module for image processing. A medium filter destroys properties less than half the size of the core filter. Large stops, such as margins and large changes in image intensity, do not affect the average intensity of the filter, although their positions can be changed by a few pixels. This linear operation of the secondary filter allows the specific type of noise to be significantly reduced. Fuzzy logic has been used across many domains to deal with uncertainty in any data. The data related to humans are mainly vague. Uncertainty must be resolved by appropriate techniques such as vague logic. Likewise, any process and method associated with such data should take this uncertainty into account when using related methods (e.g., fuzzy logic). Table 2 gives the strength and weakness of different pre-processing techniques.

Performance comparison of Segmentation

The technology of different categories used in the lung nodes are region of interest, U-Net segmentation, and morphological filtering. Due to the X-ray properties, components of different densities give different CT values in the image. Therefore, the lung area can be separated by selecting the appropriate entrance. The inspiration for

Table 2: Pre-processing strength and weakness.

Techniques	Strength	Weakness	Source
K-means Algorithm	Relatively simple to implement. Scales to large data sets.	Reduce the dimensionality of feature data by using PCA.	[67,69]
Otsu threshold	Used for nodule segmentation. To generate new system	This is fuzzy logic, not binarization.	[67,79,82,103]
		It does not fit requirements, since it is a global method	
Median filtering	Non-linear filtering technique. Median filtering can be useful to reduce noise	Difficult to treat analytically. No error propagation.	[68,71]
Fuzzy clustering method	Gives best result for overlapped data set, comparatively better than k-means algorithm.	A priapism specification of number of clusters. Euclidean distance measures can unequally weight underlying factors.	[72,83,100]

Table 3: Segmentation strength and weakness.

Techniques	Strength	Weakness	Source
Region of Interest (ROI)	It is fully automated and does not need any initialization. The union of all regions forms the entire image region.	It produces excessive over-segmentation.	[46,47,55,59,62,73,78-83,87,88,96,97]
U-Net Segmentation	Can be easily scaled to have multiple classes. Relatively easy to understand why the architecture works, if you understand how convolutions work.	Because of many layers takes significant amount of time to train.	[46,47,55,62,64,66,70,72,73,78-83,87,88,96,97]
		The architecture initially was designed to overcome the ad hoc choice of patches hyper-parameters.	
Morphological filtering	Robust accurate, independent of initialization.	It does not make use of contours; rather it separates the image into different regions.	[66,74,76,79,82,86]

Table 4: Feature extraction strength and weakness.

Techniques	Strength	Weakness	Source
Region growing	Region growing method gives better results when the homogeneity criterion is well defined and is robust against noise.	Depends on the seed point selection and is time consuming.	[66,67,69,71,72,74,81,83]
	Watershed algorithm gives a closed boundary.	Over segmentation problem.	
GLCM	It is a good approach for characterizing the texture and feature extraction techniques.	It can take very large number of possible texture calculation.	[67,71,74,94,100]
	Easy to implement.	Difficult to find the various parameters of GLCM matrices.	

this work is to effectively and quickly strengthen the lung nodes in CT films. Therefore, we suggest a Homocentric Square Filter (HSF) to overcome the weaknesses of the above methods. The main idea of the proposed method is based on the CT properties and node shape characteristics. Table 3 shows the strength and weakness of different segmentation techniques.

Performance comparison of feature extraction

The Gray Level Co-occurrence Matrix (GLCM) has proven to be a popular statistical method for extracting text from images. According to the Parallel Phenomena Matrix, Haralick defines fourteen textual features measured from the probability matrix to obtain structural statistics of remotely sensitive images. The local development algorithm is based on functional rest systems. Each image takes all the local development parameters, and the resulting features are analyzed using a complete image histogram. The maximum Eigen value is defined by two class pixels from the histogram: The ship and the background. Only one class can be calculated from the slope size map: Lower magnitude. Table 4 illustrates the strength and weakness of feature extraction techniques.

Performance comparison of classifiers

At a high level, machine learning is the study of a computer program or methodology that teaches how to improve a given task. On the subject research page, you can find machine learning through the lens of the theoretical and mathematical model of this process. However, it is most practical to learn how to create programs that demonstrate these functional improvements. There are many ways to formulate this concept, but there are often three main recognized categories: Supervised teaching, non-observational teaching, and teaching reinforcement.

Supervised learning: Oversight training is a very popular model for machine learning. It is understandable and easy to implement. This is similar to teaching a child to use flash cards.

Unsupervised learning: Learning without supervision is the opposite of learning. It has no labels. Instead, our algorithm will give you a lot of data and tools to understand the features of the data.

Performance comparison of SVM classifiers: In this section, we analyze the performance of existing state-of-art techniques for lung nodule detection and classification. Table 5 illustrates the summary of performance analysis of different SVM classifiers. The table clearly shows that three different metrics are mainly used such as accuracy, sensitivity and specificity. We notice here, the accuracy of disease prediction in [48] is very high i.e., 97% which is very higher than other SVM classifiers [49-59,70-93]. Like, the sensitivity of disease prediction in [46,54,59] is very high i.e., 100% which is very higher than other SVM classifiers. But we are not possible to get any data relevant to specificity in [48], meanwhile the specificity of disease prediction in [100] is very high i.e., 96.5% which is very higher than other SVM classifiers. Figure 15 gives the graphical representation of same performance analysis.

Performance comparison of decision Trees classifiers: In this section, we analyze the performance of existing state-of-art techniques for lung nodule detection and classification. Table 6 illustrates the summary of performance analysis of different decision trees classifiers. The table clearly shows that three different metrics are mainly used such as accuracy, sensitivity and specificity. We notice here, the accuracy of disease prediction in [84] is very high i.e., 93.4% which is very higher than other decision trees classifiers [82]. Like, the sensitivity of disease prediction in [84] is very high i.e.,77.6% which

Table 5: Comparison of SVM classifiers for lung nodule detection.

Ref. no.	Performance metrics (%)									
	A	P	SE	S	FM	R	MMMRE	RMSEE	MPRE	MPRE
[46]	**X**		X	X			X			
[48]	X									
[49]	X		X					X		X
[50]			X							
[51]			X	X			X			X
[53]			X	X						
[54]	X		X							
[56]			X	X				X		X
[57]	X									
[58]	X						X		X	
[59]			X							
[70]		X		X	X	X			X	
[71]			X							
[74]	X		X	X		X				
[75]			X						X	
[76]	X			X				X		
[79]				X						
[80]				X		X			X	
[82]	X									X
[83]				X		X		X		
[84]	X		X	X						
[88]	X		X	X		X			X	
[90]	X		X	X						
[92]	X							X	X	
[93]	X		X	X			X			X
[100]			X	X		X		X		

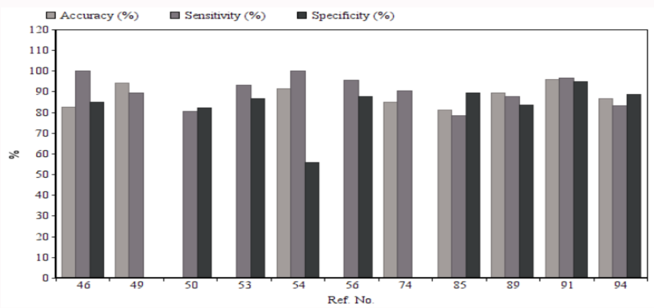

Figure 15: Performance comparison of SVM classifier for Lung nodule prediction.

is very higher than other decision trees classifiers. But we are not possible to get any data relevant to specificity in [82], meanwhile the specificity of disease prediction in [84] is very high i.e., 85.4% which is very higher than other decision trees classifiers. Figure 16 gives the graphical representation of same performance analysis.

Performance comparison of random forest classifiers: In this section, we analyze the performance of existing state-of-art techniques for lung nodule detection and classification. Table 7 illustrates the summary of performance analysis of different random

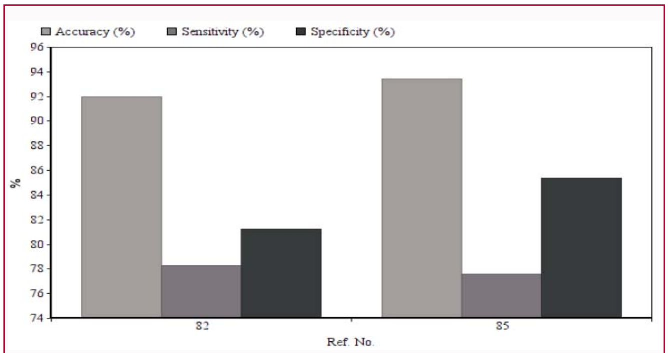

Figure 16: Performance comparison of decision tree classifier for Lung nodule prediction.

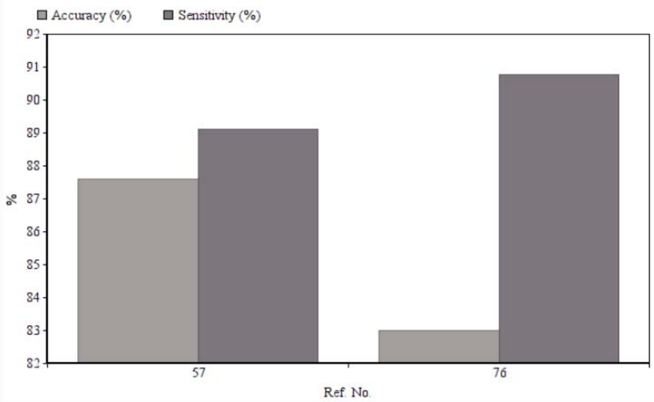

Figure 17: Performance comparison of random forest classifier for Lung nodule prediction.

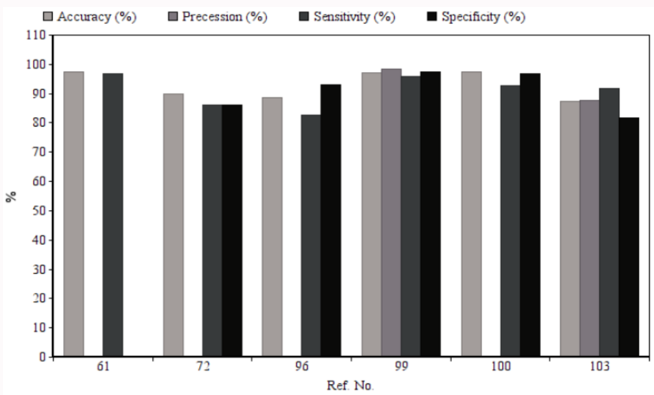

Figure 18: Performance comparison of CNN classifier for Lung nodule prediction.

forest classifiers. The table clearly shows that three different metrics are mainly used such as accuracy, sensitivity and specificity. We notice here, the accuracy of disease prediction in [57] is very high i.e., 87.6% which is very higher than other random forest classifiers [76]. Like, the sensitivity of disease prediction in [76] is very high i.e., 90.7% which is very higher than other decision trees classifiers. But we are not possible to get any data relevant to specificity in [57], meanwhile the specificity of disease prediction in [76] is very high i.e., 80% which is very higher than other decision trees classifiers. Figure 17 gives the graphical representation of same performance analysis.

Performance comparison of CNN classifiers: In this section, we

Table 6: Comparison of decision trees classifiers for lung nodule detection.

Ref. no.	Performance metrics (%)									
	A	P	SE	S	FM	R	MMRE	RMSE	MPRE	MPRE
[82]	X						X			
[84]	X		X	X				X		X

Table 7: Comparison of Random Forest classifiers for Lung nodule detection.

Ref. no.	Performance metrics (%)									
	A	P	SE	S	FM	R	MMRE	RMSE	MPRE	MPRE
[57]	X						X			
[76]	X		X					X		X

Table 8: Comparison of CNN classifiers for Lung nodule detection.

Ref. no.	Performance metrics (%)									
	A	P	SE	S	FM	R	MMR	RMSE	MMPRE	MPRE
[61]	X			X						
[72]	X		X	X				X		
[91]		X					X			
[95]	X		X	X						
[97]	X								X	
[98]	X	X	X	X	X	X		X		X
[99]	X		X	X						
[101]	X						X			X
[102]	X	X	X	X						
[104]	X						X			

Table 9: Comparison of ANN classifiers for Lung nodule detection.

Ref. no.	Performance metrics (%)									
	A	P	SE	S	FM	R	AUROC	RMSE	KAPPA	MPRE
[47]			X							
[48]	X						X			
[62]	X					X				X
[67]	X		X	X				X		
[73]			X							
[76]	X		X				X	X	X	
[80]	X		X	X						
[82]			X							
[83]	X									X
[96]	X		X			X				
[97]	X							X		

analyze the performance of existing state-of-art techniques for lung nodule detection and classification. Table 8 illustrates the summary of performance analysis of different CNN classifiers. The table clearly shows that three different metrics are mainly used such as accuracy, sensitivity and specificity. We notice here, the accuracy of disease prediction in [61] is very high i.e., 97.4% which is very higher than other CNN classifiers [72,97-104]. Like, the sensitivity of disease prediction in [61] is very high i.e., 96.8% which is very higher than other CNN classifiers. But we are not possible to get any data relevant to specificity in [61], meanwhile the specificity of disease prediction in [98] is very high i.e., 97.3% which is very higher than other CNN classifiers. Figure 18 gives the graphical representation of same performance analysis.

Performance comparison of ANN classifiers: In this section, we analyze the performance of existing state-of-art techniques for lung nodule detection and classification. Table 9 illustrates the summary of performance analysis of different ANN classifiers. The table clearly shows that three different metrics are mainly used such as accuracy, sensitivity and specificity. We notice here, the accuracy of disease prediction in [47] is very high i.e., 97% which is very higher than other CNN classifiers [48,80-97]. Like, the sensitivity of disease prediction in [76] is very high i.e., 94.7% which is very higher than other CNN classifiers. But we are not possible to get any data relevant to specificity in [47], meanwhile the specificity of disease prediction in [67] is very high i.e., 89.47% which is very higher than other ANN classifiers. Figure 19 gives the graphical representation of same

Table 10: Comparison of deep neural network classifiers for Lung nodule detection.

Ref.no.	Performance metrics (%)									
	A	P	SE	S	FM	R	MMRE	RMSE	MPRE	MPRE
[77]	X		X				X		X	
[103]	X		X	X				X		X

Table 11: Comparison of linear discriminate analysis classifiers for Lung nodule detection.

Ref. no.	Performance metrics (%)									
	A	P	SE	S	FM	R	MMRE	RMSE	MPRE	MPRE
[70]		X			X	X	X		X	
[78]	X							X		X

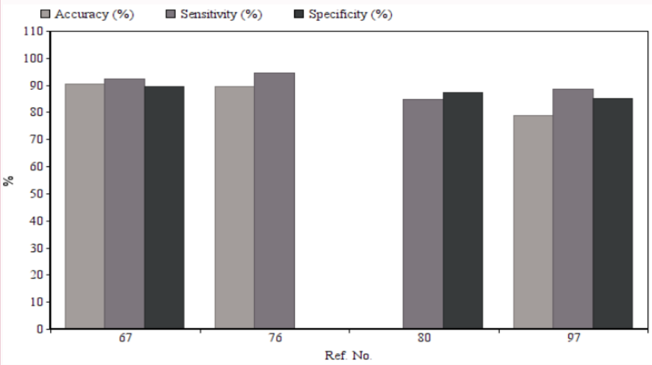

Figure 19: Performance comparison of ANN classifier for Lung nodule prediction.

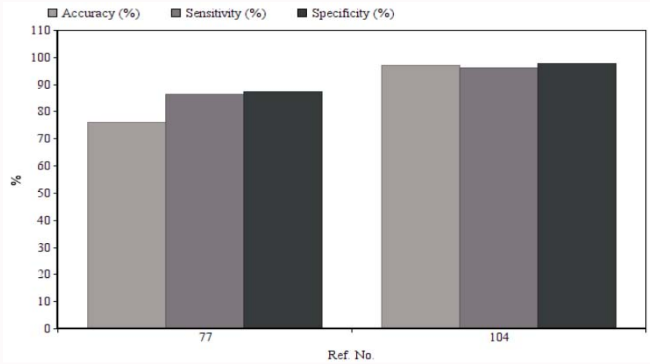

Figure 20: Graphical representation of same performance analysis.

performance analysis.

Performance comparison of deep neural network classifiers: In this section, we analyze the performance of existing state-of-art techniques for lung nodule detection and classification. Table 10 illustrates the summary of performance analysis of different deep neural network classifiers. The table clearly shows that three different metrics are mainly used such as accuracy, sensitivity and specificity. We notice here, the accuracy of disease prediction in [103] is very high i.e., 97% which is very higher than other deep neural network classifiers [77]. Like, the sensitivity of disease prediction in [103] is very high i.e., 96.2% which is very higher than other deep neural network classifiers. But we are not possible to get any data relevant to specificity in [77], meanwhile the specificity of disease prediction in [103] is very high i.e., 97.8% which is very higher than other deep neural network classifiers. Figure 20 gives the graphical representation of same performance analysis.

Performance comparison of linear discriminate analysis classifiers: In this section, we analyze the performance of existing state-of-art techniques for lung nodule detection and classification. Table 11 illustrates the summary of performance analysis of different linear discriminate analysis network classifiers. The table clearly shows that three different metrics are mainly used such as accuracy, sensitivity and specificity. We notice here, the accuracy of disease prediction in [78] is very high i.e., 93% which is very higher than other linear discriminate analysis classifiers [70]. Like, the recall of disease prediction in [70] is very high i.e., 93% which is very higher than other linear discriminate analysis classifiers. But we are not possible to get any data relevant to specificity in [78], meanwhile the force measure of disease prediction in [70] is very high i.e., 90% which is very higher than other linear discriminate analysis classifiers.

Conclusion

In this study, they conducted a classification of lung nodules diagnosis on CT images based on hybrid deep learning techniques. Examine the specific focus area and problem, the technical details of the models used, the data sources used, the processing tasks, the techniques used to enhance the data obtained, and the overall performance according to the performance measures used on each paper. They can be compared with other existing technologies in terms of deep learning effectiveness. Five key questions were identified to clarify the direction of the research. Finally, the results of the current study are summarized as follows:

RQ1: Which sources and techniques of data had been used?

The techniques used in lung nodules are classified into four they are pre-processing, segmentation, feature extraction and classifier and the majority source used is IEEE Xplore.

RQ2: How did lung nodules diagnosis improve in prior studies?

A growing lung nodule is highly likely to be a malignant one. Individuals with incidentally discovered nodules must always be instructed to present prior imaging studies for comparison, if available, and depending on the time interval, nodules stability practically abolishes the need for any further action. The relatively rapid growth rate of lung cancerous lesions forms the theoretical basis for CT images applied in the management of lung nodules.

RQ3: How is the accuracy of ML-based models recommended in prior studies calculated?

Machine learning confirms the lack of empirical research on the use of SVM, LDA, ANN, DNN, CNN, DT and RF technologies. Some ML hardware is not used in the lung nodules based on CT images domain. However, researchers are requested to conduct more empirical research on the rarely used ML technology, which further strengthens the empirical evidence for its effectiveness. In addition, ML urges researchers to explore the possibility of using outdated hardware to evaluate software development efforts.

RQ4: Is SVM able to significantly improve accuracy in comparison to state of art system techniques?

Yes, the SVM significantly improves accuracy in comparison to state of art system. As the current study confirms, the most selective performance measures (89%, 94% and 96%, respectively) are SP, A and SE. Although these measurements have been widely used in previous studies, statistical tests should also be used to avoid biased and unbalanced results.

RQ5: Did we get the same attention from researchers at different stages of the nodules process?

The classification of the different stages of the nodules process attracts the attention of researchers.

Accordingly, five study questions were considered in the present study. The most important limitation of this study is the various criteria used to evaluate the efforts made in previous studies. This difference allows us to compare the accuracy of the models recommended in this section. For example, in previous studies, performance measurements, evaluation methods, and data sets were completely different. As a feature of the future, they are improving the accuracy of lung node calculations for various projects using advanced data technology.

References

1. Diciotti S, Lombardo S, Coppini G, Grassi L, Falchini M, Mascalchi M. The LoG characteristic scale: A consistent measurement of lung nodule size in CT imaging. IEEE Trans Med Imaging. 2010;29(2):397-409.
2. Silva AC, Carvalho PC, Gattass M. Diagnosis of solitary lung nodule using texture e geometry in computerized tomography images: Preliminary results. IEEE Lat Am Trans. 2004;2(2):75-80.
3. Coppini G, Diciotti S, Falchini M, Villari N, Valli G. Neural networks for computer-aided diagnosis: Detection of lung nodules in chest radiograms. IEEE Trans Inf Technol Biomed. 2003;7(4):344-57.
4. Sofka M, Stewart CV. Location Registration and Recognition (LRR) for serial analysis of nodules in lung CT scans. Med Image Anal. 2010;14(3):407-28.
5. Yankelevitz DF, Cham MD, Farooqi AO, Henschke CI. CT-directed diagnosis of peripheral lung lesions suspicious for cancer. Thorac Surg Clin. 2007;17(2):143-58.
6. Delbeke D, Schöder H, Martin WH, Wahl RL. Hybrid imaging (SPECT/CT and PET/CT): Improving therapeutic decisions. Semin Nucl Med. 2009;39(5):308-40.
7. Niki N, Kawata Y, Kubo M. A CAD system for lung cancer based on CT image. Int Congr Ser. 2001;1230:631-8.
8. Schillaci O. Single-photon emission computed tomography/computed tomography in lung cancer and malignant lymphoma. Semin Nucl Med. 2006:36(4):275-85.
9. Ernst A, Feller-Kopman D, Herth FJ. Endobronchial ultrasound in the diagnosis and staging of lung cancer and other thoracic tumors. Semin Thorac Cardiovasc Surg. 2007;19(3):201-5.
10. Giraud P, Grahek D, Montravers F, Carette MF, Deniaud-Alexandre E, Julia F, et al. CT and 18F-Deoxyglucose (FDG) image fusion for optimization of conformal radiotherapy of lung cancers. Int J Radiat Oncol Biol Phys. 2001;49(5):1249-57.
11. Devaraj A, Cook GJR, Hansell DM. PET/CT in non-small cell lung cancer staging-promises and problems. Clin Radiol. 2007;62(2):97-108.
12. Mayer D, Bartz D, Fischer J, Ley S, del Rıo A, Thust S, et al. Hybrid segmentation and virtual bronchoscopy based on CT images. Acad Radiol. 2004;11(5):551-65.
13. Machac J, Krynyckyi B, Kim C. Peptide and antibody imaging in lung cancer. Semin Nucl Med. 2002;32(4):276-92.
14. Boroczky L, Zhao L, Lee KP. Feature subset selection for improving the performance of false positive reduction in lung nodule CAD. IEEE Trans Inf Technol Biomed. 2006;10(3):504-11.
15. Messay T, Hardie RC, Rogers SK. A new computationally efficient CAD system for pulmonary nodule detection in CT imagery. Med Image Anal. 2010;14(3):390-406.
16. Li X, Samei E, DeLong DM, Jones RP, Colsher JG, Frush DP. Toward assessing the diagnostic influence of dose reduction in pediatric CT: A study based on simulated lung nodules. In Medical Imaging 2008: Physics of Medical Imaging. International Society for Optics and Photonics. 2008;6913:69131L.
17. Chowdhury FU, Scarsbrook AF. The role of hybrid SPECT-CT in oncology: Current and emerging clinical applications. Clin Radiol. 2008;63(3):241-51.
18. Kawata Y, Niki N, Ohmatsu H, Moriyama N. Example-based assisting approach for pulmonary nodule classification in three-dimensional thoracic computed tomography images. Acad Radiol. 2003;10(12):1402-15.
19. Vijayanathan S, Butt S, Gnanasegaran G, Groves AM. Advantages and limitations of imaging the musculoskeletal system by conventional radiological, radionuclide, and hybrid modalities. Semin Nucl Med. 2009;39(6):357-68.
20. Gordin A, Golz A, Keidar Z, Daitzchman M, Bar-Shalom R, Israel O. The role of FDG-PET/CT imaging in head and neck malignant conditions: Impact on diagnostic accuracy and patient care. Otolaryngol Head Neck Surg. 2007;137(1):130-7.
21. Senan S, De Ruysscher D. Critical review of PET-CT for radiotherapy planning in lung cancer. Crit Rev Oncol Hematol. 2005;56(3):345-51.
22. Paterson A. Imaging evaluation of congenital lung abnormalities in infants and children. Radiol Clin North Am. 2005;43(2):303-23.
23. Katz S, Ferrara T, Alavi A, Torigian DA. PET, CT, and MR imaging for assessment of thoracic malignancy: Structure meets function. PET Clin. 2008;3(3):395-410.
24. Schuster DM, Alazraki N. Gallium and other agents in diseases of the lung. Semin Nucl Med. 2002;32(3):193-211.
25. Mac Manus M, Hicks RJ. The use of Positron Emission Tomography (PET) in the staging/evaluation, treatment, and follow-up of patients with lung cancer: a critical review. Int J Radiat Oncol Biol Phys. 2008;72(5):1298-306.
26. Han G, Liu X, Han F, Santika INT, Zhao Y, Zhao X, et al. The LISS--a public database of common imaging signs of lung diseases for computer-aided detection and diagnosis research and medical education. IEEE Trans Biomed Eng. 2014;2(2):648-56.
27. Nizami IF, Hasan SU, Javed IT. A wavelet frames+ K-means based automatic method for lung area segmentation in multiple slices of CT scan. 17th IEEE International Multi Topic Conference. 2014;245-8.
28. Farag AA, Abd El Munim HE, Graham JH, Farag AA. A novel approach for lung nodules segmentation in chest CT using level sets. IEEE Trans Image Process. 2013;22(12):5202-13.
29. Zhang WJ, Hu X, Liu CH, Peng SH, Zhao JM, Zou CR. A homocentric squares filter for pulmonary nodule enhancement based on the CT images. 8th International Congress on Image and Signal Processing. 2015;408-12.

30. Fazli S, Jafari M, Safaei A. Automated lung CT image segmentation using kernel mean shift analysis. 2013 8th Iranian Conference on Machine Vision and Image Processing. 2013;392-6.

31. Tariq A, Akram MU, Javed MY. Lung nodule detection in CT images using neuro fuzzy classifier. In 2013 Fourth International Workshop on Computational Intelligence in Medical Imaging (CIMI). 2013;49-53.

32. Diciotti S, Lombardo S, Falchini M, Picozzi G, Mascalchi M. Automated segmentation refinement of small lung nodules in CT scans by local shape analysis. IEEE Trans Biomed Eng. 2011;58(12):3418-28.

33. Guanglei S, Jinfeng C, Yan K. A three-dimensional ray casting method for juxta-pleural nodule segmentation in thoracic CT images. 2012 IEEE International Conference on Information and Automation. 2012;230-5.

34. Guo N, Yen RF, El Fakhri G, Li Q. SVM based lung cancer diagnosis using multiple image features in PET/CT. 2015 IEEE Nuclear Science Symposium and Medical Imaging Conference (NSS/MIC). 2015;1-4.

35. Qian Y, Guirong W. Lung nodule segmentation using EM algorithm. 2014 Sixth International Conference on Intelligent Human-Machine Systems and Cybernetics. 2014;1:20-3.

36. Chen P. Study on medical image processing technologies based on DICOM. J Comput. 2012;7(10):2354-61.

37. Elizabeth DS, Kannan A, Nehemiah HK. Computer-aided diagnosis system for the detection of bronchiectasis in chest computed tomography images. Int J Imaging Syst Technol. 2009;19(4):290-3.

38. Jeeva JB. A computer aided diagnosis for detection and classification of lung nodules. 2015 IEEE 9th International Conference on Intelligent Systems and Control (ISCO). 2015;1-5.

39. Motohiro A, Ueda H, Komatsu H, Yanai N, Mori T. Prognosis of non-surgically treated, clinical stage I lung cancer patients in Japan. Lung Cancer. 2002;36(1):65-9.

40. Mughal MN, Ikram W. Early lung cancer detection by classifying chest CT im-ages: A survey. 8th International Multitopic Conference, 2004. Proceedings of INMIC. 2004;67-72.

41. Hasling DW, Clancey WJ, Rennels GR. 1983, Strategic explanations in consultation. Int J Man Mach Stud. 2004;20(1):3-19.

42. Ballangan C, Wang X, Feng D, Eberl S, Fulham M. Lung segmentation and tumor detection from CT thorax volumes of FDG PET-CT scans by template registration and incorporation of functional information. IEEE Nucl Sci Symp Conf Rec. 2008;5349-52.

43. Kanazawa K, Kawata Y, Niki N, Satoh H, Ohmatsu H, Kakinuma R, et al. Computer-aided diagnosis for pulmonary nodules based on helical CT images. Comput Med Imaging Graph. 1998;22(2):157-67.

44. Farahani FV, Ahmadi A, Zarandi MF. Lung nodule diagnosis from CT images based on ensemble learning. 2015 IEEE Conference on Computational Intelligence in Bioinformatics and Computational Biology (CIBCB). 2015;1-7.

45. Ashwin S, Ramesh J, Kumar SA, Gunavathi K. Efficient and reliable lung nodule detection using a neural network-based computer aided diagnosis system. International Conference on Emerging Trends in Electrical Engineering and Energy Management (ICETEEEM). 2012;135-42.

46. Su H, Qian W, Sankar R, Sun X. A new knowledge-based lung nodule detection system. International Conference on Acoustics, Speech, and Signal Processing (ICASSP). 2004.

47. Ozekes S, Osman O. Computerized lung nodule detection using 3D feature extraction and learning based algorithms. J Med Syst. 2010;34(2):185-94.

48. Zheng B, Wang X, Lederman D, Tan J, Gur D. Computer-aided detection: The effect of training databases on detection of subtle breast masses. Acad Radiol. 2010;17(11):1401-8.

49. Huang YL. Computer-aided diagnosis using neural networks and support vector machines for breast ultrasonography. J Med Ultrasound. 2009;17(1):17-24.

50. Kakar M, Olsen DR. Automatic segmentation and recognition of lungs and lesion from CT scans of thorax. Computer Med Imaging Graph. 2009;33(1):72-82.

51. Wolf M, Krishnan A, Salganicoff M, Bi J, Dundar M, Fung G, et al. CAD performance analysis for pulmonary nodule detection on thin-slice MDCT scans. Int Congr Ser. 2005;1281:1104-8.

52. Campadelli P, Casiraghi E, Valentini G. Support vector machines for candidate nodules classification. Neurocomputing. 2005;68:281-8.

53. Lee SLA, Kouzani AZ, Hu EJ. Random forest-based lung nodule classification aided by clustering. Comput Med Imaging Graph. 2010;34(7):535-42.

54. Zhao L, Boroczky L, Lee KP. False positive reduction for lung nodule CAD using support vector machines and genetic algorithms. Int Congr Ser. 2005;1281(4):1109-14.

55. Dodd LE, Wagner RF, Armato III SG, McNitt-Gray MF, Beiden S, Chan HP, et al. Assessment methodologies and statistical issues for computer-aided diagnosis of lung nodules in computed tomography: Contemporary research topics relevant to the lung image database consortium. Acad Radiol. 2004;11(4):462-75.

56. Farag AA, Graham J, Elshazly S, Farag A. Data-driven lung nodule models for robust nodule detection in chest CT. 2010 20th International Conference on Pattern Recognition. 2010;2588-91.

57. Kouzani AZ, Lee SLA, Hu EJ. Lung nodules detection by ensemble classification. 2008 IEEE International Conference on Systems, Man and Cybernetics. 2008;324-9.

58. Campadelli P, Casiraghi E, Valentini G. Lung nodules detection and classification. IEEE International Conference on Image Processing 2005. 2005;1:I-1117.

59. Dehmeshki J, Chen J, Casique MV, Karakoy M. Classification of lung data by sampling and support vector machine. Conf Proc IEEE Eng Med Biol Soc. 2004;2004:3194-7.

60. Dehmeshki J, Siddique M, Lin XY, Roddie M, Costello J. Automated detection of nodules in the CT lung images using multi-modal genetic algorithm. 3rd International Symposium on Image and Signal Processing and Analysis, 2003. ISPA 2003. Proceedings of the. 2003;1:393-8.

61. Heeneman T, Hoogendoorn M. Lung nodule detection by using Deep Learning. University of Amsterdam, Research Paper. 2018.

62. Samala R, Moreno W, You Y, Qian W. A novel approach to nodule feature optimization on thin section thoracic CT. Acad Radiol. 2009;16(4):418-27.

63. Antonelli M, Yang GZ. Lung nodule detection using eye-tracking. 2007 IEEE International Conference on Image Processing. IEEE. 2007;2:II-457.

64. Retico A, Fantacci ME, Gori I, Kasae P, Golosio B, Piccioli A, et al. Pleural nodule identification in low-dose and thin-slice lung computed tomography. Comput Biol Med. 2009;39(12):1137-44.

65. Iwano S, Okada T, Koike W, Matsuo K, Toya R, Yamazaki M, et al. Semi-automatic volumetric measurement of lung cancer using multi-detector CT: Effects of nodule characteristics. Acad Radiol. 2009;16(10):1179-86.

66. Suiyuan W, Junfeng W. Pulmonary nodules 3D detection on serial CT scans. 2012 Third Global Congress on Intelligent Systems. 2012;257-60.

67. Dandıl E, Çakiroğlu M, Ekşi Z, Özkan M, Kurt ÖK, Canan A. Artificial neural network-based classification system for lung nodules on computed tomography scans. 2014 6th International Conference of Soft Computing and Pattern Recognition (SoCPaR). 2014;382-6.

68. Novo J, Gonçalves L, Mendonça AM, Campilho A. 3D lung nodule candidate detection in multiple scales. 2015 14th IAPR International

Conference on Machine Vision Applications (MVA). 2015;61-4.

69. Zhai Z, Shi D, Cheng Y, Guo H. Computer-aided detection of lung nodules with fuzzy min-max neural network for false positive reduction. 2014 Sixth International Conference on Intelligent Human-Machine Systems and Cybernetics. 2014;1:66-9.

70. Agarwal R, Shankhadhar A, Sagar RK. Detection of lung cancer using content based medical image retrieval. 2015 Fifth International Conference on Advanced Computing & Communication Technologies. 2015;48-52.

71. Kumar SA, Ramesh J, Vanathi PT, Gunavathi K. Robust and automated lung nod-ule diagnosis from CT images based on fuzzy systems. In 2011 International Conference on Process Automation, Control and Computing. IEEE. 2011;1-6.

72. Nagata R, Kawaguchi T, Miyake H. A computer-aided diagnosis system for lung nodule detection in chest radiographs using a two-stage classification method based on radial gradient and template matching. In 2013 6th International Conference on Biomedical Engineering and Informatics. IEEE. 2013;80-5.

73. Thomas RA, Kumar SS. Automatic detection of lung nodules using classifiers. In 2014 International Conference on Control, Instrumentation, Communication and Computational Technologies (ICCICCT). IEEE. 2014;705-10.

74. Han F, Zhang G, Wang H, Song B, Lu H, Zhao D, et al. A texture feature analysis for diagnosis of pulmonary nodules using LIDC-IDRI database. In 2013 IEEE International Conference on Medical Imaging Physics and Engineering. IEEE. 2013;14-8.

75. Tartar A, Akan A, Kilic N. A novel approach to malignant-benign classification of pulmonary nodules by using ensemble learning classifiers. Annu Int Conf IEEE Eng Med Biol Soc. 2014;4651-4.

76. Kumar D, Wong A, Clausi DA. Lung nodule classification using deep features in CT images. In 2015 12th Conference on Computer and Robot Vision. IEEE. 2015;133-8.

77. Aggarwal P, Sardana HK, Vig R. Content-based medical image retrieval using patient's semantics with proven pathology for lung cancer diagnosis. In Fifth International Conference on Advances in Recent Technologies in Communication and Computing (ARTCom 2013). IEEE. 2013.

78. Ying W, Tong J, Ming-Xiu L. Autonomous detection of solitary pulmonary nodules on CT images for computer-aided diagnosis. In 2011 Chinese Control and Decision Conference (CCTC). IEEE. 2011;4054-9.

79. Chen S, Suzuki K. Computerized detection of lung nodules by means of "virtual dual-energy" radiography. IEEE Trans Biomed Eng. 2013;60(2):369-78.

80. Puentes MAM, Furst J, Raicu DS. Machine-sourced segmentations *vs.* expert-sourced segmentations for the classification of lung nodules with outlier removal. In 2014 13th International Conference on Machine Learning and Applications. 2014;510-5.

81. Hadavi N, Nordin MJ, Shojaeipour A. Lung cancer diagnosis using CT-scan images based on cellular learning automata. In 2014 International Conference on Computer and Information Sciences (ICCOINS). IEEE. 2014;1-5.

82. Smith E, Stein P, Furst J, Raicu DS. Weak segmentations and ensemble learning to predict semantic ratings of lung nodules. In 2013 12th International Conference on Machine Learning and Applications. IEEE. 2013;2:519-24.

83. Parveen SS, Kavitha C. Detection of lung cancer nodules using automatic region growing method. In 2013 Fourth International Conference on Computing, Communications and Networking Technologies (ICCCNT). IEEE. 2013;1-9.

84. Krewer H, Geiger B, Hall LO, Goldgof DB, Gu Y, Tockman M, et al. Effect of texture features in computer aided diagnosis of pulmonary nodules in low-dose computed tomography. In 2013 IEEE International Conference on Systems, Man, and Cybernetics. IEEE. 2013;3887-91.

85. Chunran Y, Yuanvuan W, Yi G. Automatic detection and segmentation of lung nodule on CT images. In 2018 11th International Congress on Image and Signal Processing, Biomedical Engineering and Informatics (CISP-BMEI). IEEE. 2018;1-6.

86. Paing MP, Choomchuay S. A computer aided diagnosis system for detection of lung nodules from series of CT slices. In 2017 14th International Conference on Electrical Engineering/Electronics, Computer, Telecommunications and Information Technology (ECTI-CON). IEEE. 2017;302-5.

87. Wei G, Ma H, Qian W, Zhao X. A content-based image retrieval scheme for identifying lung nodule malignancy levels. In 2017 29th Chinese Control and Decision Conference (CCTC). IEEE. 2017;3127-30.

88. Rendon-Gonzalez E, Ponomaryov V. Automatic lung nodule segmentation and classification in CT images based on SVM. In 2016 9th International Kharkiv Symposium on Physics and Engineering of Microwaves, Millimeter and Submillimeter Waves (MSMW). IEEE. 2016;1-4.

89. Yan R, Ashrafinia S, Park S, Lee J, Chu LC, Lin CT, et al. The use of low-dose CT intra-and extra-nodular image texture features to improve small lung nodule diagnosis in lung cancer screening. In 2017 IEEE Nuclear Science Symposium and Medical Imaging Conference (NSS/MIC). IEEE. 2017;1-4.

90. Wang Z, Xin J, Sun P, Lin Z, Yao Y, Gao X. Improved lung nodule diagnosis accuracy using lung CT images with uncertain class. Comput Methods Programs Biomed. 2018;162:197-209.

91. Liu X, Hou F, Qin H, Hao A. Multi-view multi-scale CNNs for lung nodule type classification from CT images. Pattern Recognition. 2018;77:262-75.

92. Nishio M, Nagashima C. Computer-aided diagnosis for lung cancer: Usefulness of nodule heterogeneity. Acad Radiol. 2017;24(3):328-36.

93. Javaid M, Javid M, Rehman MZU, Shah SIA. A novel approach to CAD system for the detection of lung nodules in CT images. Comput Methods Programs Biomed. 2016;135:125-39.

94. Xie Y, Zhang J, Xia Y, Fulham M, Zhang Y. Fusing texture, shape and deep model-learned information at decision level for automated classification of lung nodules on chest CT. Information Fusion. 2018;42:102-10.

95. Zheng G, Han G, Soomro NQ. An inception module CNN classifiers fusion method on pulmonary nodule diagnosis by signs. Tsinghua Sci Technol. 2019;25(3):368-83.

96. Mekali V, Girijamma HA. An fully automated CAD system for Juxta-Vacular nodules segmentation in CT scan images. In 2019 3rd International Conference on Computing Methodologies and Communication (ICCMC). IEEE. 2019;917-24.

97. Yan H, Lu H, Ye M, Yan K, Xu Y, Jin Q. Improved Mask R-CNN for Lung Nodule Segmentation. In 2019 10th International Conference on Information Technology in Medicine and Education (ITME). IEEE. 2019;137-41.

98. Abraham GK, Bhaskaran P, Jayanthi VS. Lung nodule classification in CT images using convolutional neural network. In 2019 9th International Conference on Advances in Computing and Communication (ICACC). IEEE. 2019;199-203.

99. Zhai P, Tao Y, Chen H, Cai T, Li J. Multi-task learning for lung nodule classification on chest CT. IEEE Access. 2020;8:180317-27.

100. Wang Y, Yue S, Li Q, Li J, Wang H. Research on technologies of computer aided diagnosis for solitary pulmonary nodule based on CT images. In 2019 IEEE International Instrumentation and Measurement Technology Conference (I2MTC). IEEE. 2019;1-5.

101. Han C, Kitamura Y, Kudo A, Ichinose A, Rundo L, Furukawa Y, et

al. Synthesizing diverse lung nodules wherever massively: 3D multi-conditional GAN-based CT image augmentation for object detection. In 2019 International Conference on 3D Vision (3DV). IEEE. 2019;729-37.

102. Xie H, Yang D, Sun N, Chen Z, Zhang Y. Automated pulmonary nodule detection in CT images using deep convolutional neural networks. Pattern Recognition. 2019;85:109-19.

103. Rahman MS, Shill PC, Homayra Z. A New method for lung nodule detection using deep neural networks for CT images. In 2019 International Conference on Electrical, Computer and Communication Engineering (ECCE). IEEE. 2019;1-6.

104. Cao H, Liu H, Song E, Ma G, Xu X, Jin R, et al. A two-stage convolutional neural networks for lung nodule detection. IEEE J Biomed Health Inform. 2020;24(7):2006-15.