IJRAR.ORG E-ISSN: 2348-1269, P-ISSN: 2349-5138

INTERNATIONAL JOURNAL OF RESEARCH AND ANALYTICAL REVIEWS (IJRAR) | IJRAR.ORG

An International Open Access, Peer-reviewed, Refereed Journal

A Review On AI Based Lung Cancer Detection

[1]Anjana Krishnakumar, [2]Dr. Kala. L

[1]M. Tech Student, [2]Associate Professor
[1]Electronics and Communication Department,
[1]NSS College of Engineering, Palakkad, India

Abstract: Lung cancer is a major public health concern that affects millions of people worldwide. It is the leading cause of cancer-related deaths globally, with a high mortality rate due to late-stage diagnosis. Early detection is crucial for improving patient outcomes, and advancements in technology have led to the development of various methods for detecting lung cancer. This review paper examines the recent techniques used for lung cancer detection, including traditional methods such as chest X-rays and CT scans, as well as emerging technologies such as Artificial Intelligence (AI) based models, including Res-Net, U-Net, and Dense-Net. The advantages and limitations of each approach are discussed, along with their potential applications in clinical settings. The paper also addresses challenges and future directions for research, such as the need for larger and more diverse datasets to train and validate these models by summarizing 10 journal papers based on the recent developments in the field of AI. In short, this review paper provides valuable insights into the latest developments in lung cancer detection, with the aim of improving patient outcomes and survival rates through earlier detection and intervention.

Keywords: Artificial- Intelligence(AI), Res-Net, U-Net, Dense-Net

Introduction

Lung cancer is one of the most common types of cancer worldwide and is responsible for more deaths than any other type of cancer. It is a type of cancer that starts in the lungs, which are a pair of spongy organs in the chest that play a crucial role in the respiratory system. The most common cause of lung cancer is tobacco smoke, including cigarette, cigar, and pipe smoke. Other risk factors for lung cancer include exposure to secondhand smoke, exposure to radon gas, exposure to certain chemicals and substances, such as asbestos and diesel exhaust, and a family history of lung cancer. Symptoms of lung cancer can include a persistent cough, coughing up blood, shortness of breath, chest pain, hoarseness, unexplained weight loss, and fatigue. Treatment for lung cancer depends on the type and stage of cancer, as well as the patient's overall health. Early detection of lung tumors is done by using many imaging techniques such as Computed Tomography (CT), Sputum Cytology, Chest X-ray, and Magnetic Resonance Imaging (MRI). Detection means classifying tumors into two classes (i)non-cancerous tumors (benign) and (ii)cancerous tumors (malignant). The chance of survival at the advanced stage is less when compared to the treatment and lifestyle to survive cancer therapy when diagnosed at the early stage of cancer. Manual analysis and diagnosis systems can be greatly improved with the implementation of AI based image processing techniques. With the advancement in computer vision, deep learning techniques are also developed which help a lot of researchers in the early diagnosis of cancer. The neural network plays a key role in the recognition of cancer cells among normal tissues, which in turn provides an effective tool. The cancer treatment will be effective only when the tumor cells are accurately separated from the normal cells. Classification of the tumor cells and training of the neural network forms the basis for deep learning-based cancer diagnosis. Recently, multiple studies have proposed using Artificial Intelligence (AI), and in particular Deep Learning, as a tool to characterize pulmonary nodules, and thereby potentially decrease the number of scans needed to arrive at a benign or malignant diagnosis.

1.1. Methods for Tumor Detection

a) Earlier used methods:

- CT is a highly sensitive imaging modality that is widely used for the detection and diagnosis of lung cancer. Here are some key points about the use of CT in detecting lung cancer:
- CT can detect lung nodules: Lung nodules are small growths on the lung that can be either benign or malignant. It can detect nodules as small as a few millimeters in size, which makes it an effective tool for the early detection of lung cancer.
- CT can distinguish between benign and malignant nodules: CT can help differentiate between benign and malignant nodules based on their size, shape, and density. For example, malignant nodules tend to have irregular shapes, spiculated margins, and higher densities than benign nodules.
- CT scan stage lung cancer: CT can help determine the stage of lung cancer by assessing the size of the excrescence, its position within the lung, and whether it has spread to near nodes or other organs.
- CT can guide biopsy and treatment: CT can be used to guide biopsy procedures, allowing doctors to obtain tissue samples from suspicious areas within the lung. It can also be used to guide radiation therapy and other treatments for lung cancer.
- CT has limitations: While CT is highly sensitive, it is not always specific, which means that it can sometimes detect abnormalities that are not cancerous. This can lead to gratuitous testing and procedures. It also exposes patients to ionizing radiation, which can increase the risk of cancer over time. CT is a valuable tool for the detection and diagnosis of lung cancer. However, it is important to weigh the benefits and risks of CT screening and to consider other factors such as an individual's age, smoking history, and overall health when determining whether CT is appropriate for lung cancer screening.

While X-ray imaging is commonly used to diagnose a variety of lung conditions, including lung cancer, it is not as effective as CT for detecting early-stage lung cancer. Here are some key points about the use of X-ray imaging in detecting lung cancer:

- X-rays can detect abnormalities in the lungs: X-rays use ionizing radiation to create images of the lungs, allowing doctors to detect abnormalities such as nodules, masses, or other growths.
- X-rays are not as sensitive as CT for detecting lung cancer: While X-rays can detect lung cancer, they are not as sensitive as CT for detecting early-stage of lung cancer. This is because X-rays produce less detailed images of the lungs than CT, making it more difficult to distinguish between cancerous and non-cancerous abnormalities.
- X-rays may be used as a screening tool: Despite its limitations, X-ray imaging may still be used as a screening tool for individuals at high risk for lung cancer, such as current or former smokers. However, the American Cancer Society does not recommend routine X-ray screening for lung cancer, as it has not been shown to reduce mortality.
- X-rays may be used to monitor the progression of lung cancer: X-rays may be used to monitor the growth and spread of lung cancer, as well as to evaluate the effectiveness of treatment. In summary, while X-ray imaging can detect lung cancer, it is not as sensitive as CT for detecting early stage lung cancer. CT is currently the preferred imaging modality for lung cancer screening and diagnosis. X-rays use low levels of radiation to produce images of the chest and can help identify abnormalities such as nodules or masses that could be cancerous.

However, X-rays have limitations in detecting small nodules and cannot distinguish between benign and malignant lesions. As a result, they are often used in conjunction with other imaging modalities such as CT scans. Another method that has been used for detecting lung cancer is sputum cytology, which involves examining a sample of mucus coughed up from the lungs under a microscope to look for cancer cells. This method is not only accurate but is also non-invasive which is limited and it may miss some cases of lung cancer. Bronchoscopy, which involves inserting a thin, flexible tube through the nose or mouth and into the lungs to visualize the airways and take tissue samples for analysis, has also been used to detect lung cancer. However, this method requires sedation and carries a risk of complications, and is usually reserved for cases where other imaging or diagnostic tests are inconclusive.

b) Recent methods:

In recent years, advancements in imaging technology and the development of AI-based algorithms have led to more accurate and non-invasive methods for detecting lung cancer, such as low-dose CT screening and deep learning models. Here are some of the recently used early lung cancer detection methods:

- Low-Dose Computed Tomography (LDCT): LDCT is a type of CT scan that uses a lower dose of radiation than a standard CT scan. LDCT is effective in detecting lung cancer at an early stage and is currently the most widely used screening method for individuals at high risk for lung cancer.
- Blood tests: Blood tests that analyze biomarkers have shown promise in detecting lung cancer at an early stage. For example, a blood test that measures levels of the protein biomarker LG3BP (Galectin-3-binding protein) has been shown to detect early-stage lung cancer with high accuracy.
- Breath tests: Breath tests that analyze Volatile Organic Compounds (VOCs) are being studied for their potential use in detecting lung cancer at an early stage. For example, a recent study found that a breath test that analyzed a panel of VOCs was able to detect early-stage lung cancer with high accuracy.
- Liquid biopsies: Liquid biopsies that analyze circulating tumor cells (CTCs) and cell-free DNA (cfDNA) have shown promise in detecting lung cancer at an early stage. For example, a recent study found that a liquid biopsy that analyzed both CTCs and cfDNA was able to detect early stage lung cancer with high accuracy.

- Artificial intelligence-based methods: Deep learning models and other AI-based methods are being developed for the early detection of lung cancer. These models can analyze CT scans and other imaging data, as well as biomarkers and other clinical data, to identify individuals who may be at high risk for developing lung cancer.

Overall, early detection of lung cancer is critical for improving treatment outcomes and survival rates. Emerging methods such as LDCT, biomarkers, breath tests, liquid biopsies, and AI-based methods are promising approaches that may lead to earlier detection of lung cancer in the future. AI-based methods have shown great potential for tumor detection in medical imaging, and have been applied to various imaging modalities such as MRI, CT, and Ultrasound. Here are some common recent AI-based methods for tumor detection:

- CNN: CNN is a type of deep learning algorithm that can extract relevant features from medical images, which can then be used to classify images as either containing a tumor or not. CNNs have been used in various studies for tumor detection in medical imaging.
- Segmentation methods: Segmentation methods can be used to separate the tumor region from the rest of the image. Various techniques, such as thresholding, region growing, and graph cuts, have been used for tumor segmentation. Segmentation can improve the accuracy of tumor detection and characterization.
- Radiomics: Radiomics is a technique that extracts a large number of quantitative features from medical images, such as texture, shape, and intensity. These features can be used to train machine-learning models for tumor detection and classification. Radiomics has been applied to various imaging modalities, including MRI, CT, and Positron Emission Tomography (PET).
- Transfer learning: Transfer learning involves using a pre-trained deep learning model, such as a CNN, and fine-tuning it on medical images for tumor detection. This approach can reduce the need for large training datasets and improve the accuracy of tumor detection.
- Ensemble methods: Ensemble methods involve combining the results of multiple AI-based models to improve the accuracy of tumor detection. Ensemble methods have been used in various studies for tumor detection in medical imaging.

AI-based methods have shown great potential for tumor detection in medical imaging. These methods can improve the accuracy and efficiency of tumor detection, which can lead to earlier diagnosis and improved treatment outcomes for patients. AI has also shown great potential in improving the accuracy and efficiency of lung cancer detection. There are several approaches to developing AI-based lung cancer detection systems, including deep learning, machine learning, and computer vision. Deep learning, specifically CNNs, has become a popular approach for AI-based lung cancer detection. CNNs are trained on large datasets of lung images, such as CT scans, to automatically learn the features that are most relevant for detecting lung cancer. One of the challenges in developing an AI-based lung cancer detection system is the lack of large, annotated datasets. However, there are several publicly available datasets, such as the LUNA-16 dataset and the LIDC-IDRI dataset, which can be used for training and validating AI models. Once a CNN model is trained, it can be used for detecting lung cancer in new patient scans. The model can analyze the scan and identify areas of concern, such as suspicious nodules or masses, and provide a diagnosis. AI-based lung cancer detection systems have the potential to assist radiologists in making more accurate and efficient diagnoses. They can also help with early detection, which can lead to better treatment outcomes for patients.

1.2. Types of Convolutional Neural Network Architectures

Res-Net

Res-Net (short for Residual Network) is a type of deep-learning neural network that's effective in detecting malignant lung nodes on CT images. Residual Networks, or Res-Nets, learn residual functions concerning the subcaste inputs, rather than learning unreferenced functions. Rather than hoping each few stacked layers directly fit a desired underlying mapping, residual nets let these layers fit a residual mapping. They mound residual blocks on top of each other to form a network. Some of the crucial points about the use of Res-Net in detecting malignant lung nodes are as follows:

- Res-Net can detect subtle features of lung nodes. It is able of detecting subtle features of lung nodes that may not be visible to the mortal eye or other machine learning algorithms. This makes it an important tool for relating malignant nodes at an early stage.
- Res-Net can distinguish between benign and malignant nodes Res-Net has been trained on large datasets of CT images to distinguish between benign and malignant nodes grounded on their size, shape, texture, and other features. This allows it to directly classify nodes as either cancerous or non-cancerous.
- Res-Net can reduce false cons, or the identification of non-cancerous nodes as cancerous can lead to gratuitous testing and procedures. Res-Net has been shown to reduce false cons and improve the accuracy of lung nodule detection.
- Res-Net can aid in diagnosis and treatment planning: Res-Net can provide radiologists with additional information to aid in the diagnosis and treatment planning for lung cancer patients. For example, Res-Net can help determine the size and position of lung nodes, as well as whether they've spread to near lymph nodes or other organs.

U-Net

U-Net is a type of deep-learning neural network that is effective in detecting malignant lung nodules on CT images. In CNN, the image is converted into a vector which is largely used in classification problems. But in U-Net, an image is converted into a vector and also the same mapping is used to convert it again to an image. This reduces the deformation by conserving the original structure of the image. Here are some key points about the use of U-Net in detecting malignant lung nodules:

- U-Net can segment the lung region accurately: U-Net has a unique architecture that allows it to accurately segment the lung region in CT images. This segmentation is an important step in detecting malignant lung nodules, as it helps to isolate the nodules from the rest of the lung tissue.
- U-Net can identify subtle features of lung nodules: U-Net has been trained on large datasets of CT images to identify subtle features of lung nodules that may not be visible to the human eye or other machine learning algorithms. This allows it to accurately detect malignant nodules at an early stage.
- U-Net can improve accuracy and reduce false positives: U-Net has been shown to improve the accuracy of lung nodule detection and reduce false positives, or the identification of non-cancerous nodules as cancerous. This can reduce unnecessary testing and procedures for patients.
- U-Net can assist radiologists in diagnosis and treatment planning: U-Net can provide radiologists with additional information to aid in the diagnosis and treatment planning for lung cancer patients. For example, U-Net can help determine the size and location of lung nodules, as well as whether they have spread to nearby lymph nodes or other organs.

Dense-Net

Dense-Net is a type of deep learning architecture that was introduced in 2017 by Gao Huang et al. It is a CNN that has shown excellent performance in image classification tasks. The key innovation of Dense-Net is its use of dense connections between layers. In a traditional CNN, each layer receives only the output of the previous layer. However, in a Dense-Net, each layer receives the output of all preceding layers. This means that the feature maps learned by each layer can be reused by all subsequent layers, allowing for better feature propagation and gradient flow. Dense-Net is composed of several dense blocks, each of which contains multiple layers with dense connections. In addition to the dense blocks, there are also transition layers that reduce the spatial dimensions of the feature maps before passing them to the next dense block. One of the advantages of Dense-Net is its ability to learn more compact and discriminative feature representations while reducing the number of parameters compared to other CNN architectures. This makes it more computationally efficient and easier to train with limited resources. Dense-Net has been successfully applied to a wide range of image classification tasks, including medical image analysis, where it has been used for lung cancer detection, mammography, and skin lesion classification.
Dense-Net (short for Dense Convolutional Network) is another type of deep learning neural network that is effective in detecting malignant lung nodules on CT images. Here are some key points about the use of Dense-Net in detecting malignant lung nodules:

- Dense-Net can learn features across different scales: Dense-Net has a unique architecture that allows it to learn features across different scales in CT images. This means it can detect both subtle and large-scale features of lung nodules.
- Dense-Net can distinguish between benign and malignant nodules: Dense-Net has been trained on large datasets of CT images to distinguish between benign and malignant nodules based on their size, shape, texture, and other features. This allows it to accurately classify nodules as either cancerous or non-cancerous.
- Dense-Net can reduce false positives: False positives, or the identification of non-cancerous nodules as cancerous, can lead to unnecessary testing and procedures. Dense-Net has been shown to reduce false positives and improve the accuracy of lung nodule detection.
- Dense-Net can assist radiologists in diagnosis and treatment planning: Dense-Net can provide radiologists with additional information to aid in the diagnosis and treatment planning for lung cancer patients. For example, Dense-Net can help determine the size and location of lung nodules, as well as whether they have spread to nearby lymph nodes or other organs. Dense-Net is a powerful and efficient deep learning architecture that has shown state-of-the-art performance in many image classification tasks. Its dense connections and efficient use of parameters make it well-suited for medical image analysis and other applications where computational resources are limited.

1.3. Comparison of Res-Net and U-Net with Dense-Net Architecture

While Res-Net and U-Net are effective deep learning models for image segmentation and classification, they have some drawbacks compared to Dense-Net. Here are some of the cons of Res-Net and U-Net when compared to Dense-Net:

- Res-Net requires a lot of memory: The architecture of Res-Net involves stacking many layers, which requires a lot of memory. This can make it difficult to train on large datasets or computers with limited resources.
- Res-Net may struggle with vanishing gradients: The architecture involves residual connections, which can help with training deep networks. However, it may also struggle with vanishing gradients, which can make it difficult to learn from certain layers.
- U-Net may overfit small datasets: U-Net is a popular architecture for image segmentation, but it may overfit small datasets. This can lead to poor generalization performance on new, unseen images.
- U-Net may struggle with large-scale features: U-Net's architecture involves contracting and expanding paths, which are good for detecting small-scale features but may struggle with largescale features such as tumors.

In comparison, Dense-Net has some advantages over Res-Net and U-Net:

- Dense-Net can use memory more efficiently: The architecture involves densely connecting layers, which can reduce the amount of memory required for training. This makes it easier to train on large datasets or computers with limited resources.
- Dense-Net can prevent vanishing gradients: The architecture involves feature reuse, which can prevent vanishing gradients and improve training performance.
- Dense-Net can learn features across different scales: The densely connected layers can learn features across different scales, which is important for detecting both small-scale and large-scale features in images.
- Dense-Net can reduce overfitting: The feature reuse in Dense-Net can also reduce overfitting, which improves generalization performance on new, unseen images. Overall, while Res-Net and U-Net are powerful deep learning models, the Dense-Net architecture has some advantages that make it particularly well-suited for image segmentation and classification tasks, such as the detection of malignant lung nodules.

2. Literature Review

In the short survey [1], Jieli Zhou and Hongyi Xin introduced the importance of lung cancer management and then summarized the various artificial intelligence methods currently in use, mostly deep learning-based lung nodule detection using CT imaging data. They introduced representative deep learning methods for each step of the computer-aided-diagnostics workflow, namely data preprocessing, lung nodule detection, and lung nodule classification. Representative datasets are also discussed. In addition, they have focused on emergent artificial intelligent methods besides CT imaging-based deep learning models. It was reported that in many recent works, clinical, physiological, and genomic data have been also shown to be helpful for lung cancer management. Finally, they suggested three emergent AI methods for fighting lung cancer, privacy-concerned federated learning models, multi-modal deep learning models combining data from different modalities, and interpretable deep learning models that combine neural networks with domain knowledge from radiologists.

In this paper [2], Ying Chen and Yerong Wang introduced Lung Dense Deep Convolutional Neural Network (LDDNet) for lung segmentation. Lung segmentation algorithms play an important role in lung cancer detection systems and directly affect the accuracy of lung cancer verification and recognition. The grayscale and texture features of the CT image of the lung are utilized by LDDNet. The high accuracy and robustness of lung CT Images can be achieved by LDDNet. Using image preprocessing and no image preprocessing as contrast proves that some special image preprocessing methods like median filter, Laplacian filter, and so on, will promote the CT lung parenchyma segmentation results of LDDNet. In contrast, some will reduce the accuracy of segmentation for instance enhanced contrast, etc. Finally, a better segmentation result is achieved in terms of accuracy and robustness. With LDDNet, the final result is improved compared to most of the traditional lung segmentation methods and deep convolutional networks for instance VGG, U-Net, ResNet, and so on. Therefore, the method of segmentation of lung CT images will continue to be studied for clinically specific applications. The goal was to improve the segmentation accuracy of lung CT images, furthermore to help doctors' clinical diagnoses, and promote medical progress better.

In this paper [3], Swati Mukherjee and Prof. S. U. Bohrahas state to use of the profound neural network system to improve the chances of tumor identification. Here, supervised learning approaches are utilized with NSCLC Radio genomics lung malignancy CT picture dataset. A framework is built that comprises numerous steps, for example, image extraction, pre-processing, binarization, thresholding, segmentation, and feature extraction. It is an application that will take input as the CT scan images and will predict the possibilities of the malignancy and its stages using deep learning. The proposed research work has dealt with the DICOM dataset and utilized a profound Convolutional neural system for accomplishing high precision. Various relevant works are done on this disease and attempts to use the best image pre-processing methods, feature extraction, and deep learning mechanism to get more accurate prediction results were studied. Ultimately, a profound neural system approach is utilized to achieve more accurate precision in the discovery of lung malignancy and precisely anticipate stages.

In this paper [4], S. Sasikala, and M. Bharathi stated a convolutional neural network-based system that was implemented to detect the malignancy tissues present in the input lung CT image. Lung images with different shapes and sizes of the cancerous tissues have been fed at the input for training the system. The proposed system was able to detect the presence and absence of cancerous cells with an accuracy of about 96%. The accuracy of Lung cancer detection with the proposed convolutional neural network-based method was compared with that obtained by previous works. In this proposed work, the specificity obtained is 100% which shows that there is no false positive detection. Also, the accuracy, sensitivity, and specificity of the proposed system are high when compared to previously available conventional neural network-based systems. Soon, the system will be trained with large datasets to diagnose the type of cancer with its size and shape. The overall accuracy of the system can be improved using a 3D Convolutional Neural Network and also by improving the hidden neurons with the deep network.

Detection of the pulmonary nodules automatically is critical for the early diagnosis and prevention of lung cancer. CT is an effective and provident lung cancer detection method. In CT images, the size and shape of pulmonary nodes appear different, and some nodes appear analogous to the surrounding tissues. Thus, the automatic localization of pulmonary nodes in CT images is a challenging task. In this paper [5], Guanglu Zhang and Hongjung Zhang proposed an attention-embedded three-dimensional convolutional neural network for pulmonary nodule detection. Specifically, 1) channel-spatial attention guides 3D ResNet to down sample the input 3D CT patch. The channel pays attention to important features and the space in the region of interest. The two form a complementary feature extraction mechanism to effectively help the global flow of information in the network and upgrade the feature maps to extract the context features of the nodule. 2) The fusion model of the feature pyramid is changed by the channel-spatial attention module which adaptively adjusts the pixel-level weight between the features and extracts multi-scale representative

node features. The results revealed that the attention-guided network could extract the multi-scale representative features of nodes, and the average sensitivity was 97.7%. The expansive trials demonstrate that the proposed approach can effectively improve the detection sensitivity and control the number of false positive nodes, which have clinical operation value and a certain reference value. 3) To replace the standard convolution of ResNet, the deep separable convolution was used by reducing the time cost and improving the effectiveness of model training which ensured the model's performance.
4) Different characteristic layers corresponded to two sizes of anchors to adapt the distribution of the nodule scale, the number of anchor frames was reduced and the network sensitivity is improved under the condition of ensuring the detection rate of nodules.

In this study [6], Kehong Liu proposed an improved lung nodule detection method based on the YOLOv5 algorithm to tackle the challenges confronted when using deep learning methods for lung nodule detection in CT images. Initially, the SPP-Net with multi-convolutional layers based on Stochastic Pooling was improved to optimize the feature extraction effect, highlighting strong features while retaining the less differentiated features. Secondly, he used the BiFPN (Weighted Bi-directional Feature Pyramid Network) structure for multi-scale feature fusion to reduce redundant computation. Finally, the original loss function GIoU (Generalized Intersection over Union) is replaced by the EIoU (Efficient Intersection over Union) function, which speeds up the convergence speed and improves the robustness. The algorithm was able to meet the real-time requirements with low computational cost, which improves the localization accuracy of lung nodules. The detection method has been compared with other deep learning detection methods in experiments and obtained an accuracy of 96.1% and recall of 93.3%, which can effectively improve the detection performance of lung nodules compared with the traditional YOLO-v5. This work still comes in its early stage. In the future, compression of the model, including channel pruning and parameter quantization to reduce the number of parameters and improve the detection speed will be tried. Improving the accuracy of the model on the premise of a small number of parameters and fast inference speed will be considered in the future.

In this paper [7], Weilun Wang and Goutam Chakraborty presented a 3D Multi-scale Dense-Net to classify the grade of malignancy of pulmonary nodules. Through the observation of CT image data, they found that for some small nodules, it is impossible to extract their morphological features due to their small size. The aim is to convert the original CT image data into three different scales and input them into three parallel 3D densely-connected convolutional networks i.e. Dense-Net blocks.
The extracted features from the last layer of the three networks were concatenated so as to classify the grade of malignancy of the pulmonary nodules. In this way, the morphological features of small nodes can be better obtained without affecting the feature extraction of large nodes. In this study, 1882 samples from the dataset of the Lung Image Database Consortium (LIDC) were used for training and testing. Overall, they have achieved 68.5% accuracy for the task of malignancy grades classification.

The objective of this study [8], stated by Alex Ede Danku and Eva H. Dulf was to analyze different types of cancer diagnosing methods that have been developed and tested using image processing methods. The analyzed factors are training parameters, image processing technique, and the obtained performances. This survey can be of significant value to researchers and professionals in medicine and computer science, highlighting areas where there are opportunities to make significant new contributions. The results of the studies which are analyzed have high accuracy and, in the future, might even start to be used in hospitals over the world. The biggest benefit is that mistakes made during diagnosis is to be reduced, and the survival chance of cancer patients will increase. Although it is a powerful tool, the main disadvantage which occurs is that each of these applications is working on certain scenarios and certain types of cancers. The reliability of such tools is considered to be small; a large number of tools is required to have a proper diagnosis. Technology has come far, but there is still room for progress and some technological advances have to be made before the diagnosis can be safely automated.

Lung nodule classification is the key link to early lung cancer screening. Early lung cancer screening through medical imaging technology can not only improve the diagnosis efficiency but also avoid the pain of patients caused by puncture sampling. In this paper [9], Gai Li and Wei Zhou have stated the wavelet de-noising analysis method which is applied to the deep learning model, and the fusion feature map with rich semantic information is obtained through convolution, pooling, and other operations. To realize the automatic detection of pulmonary nodules, it is necessary to extract the features manually for the classification of pulmonary nodules. Based on big data, the CNN is optimized by a genetic algorithm to improve its accuracy. By optimizing the detection algorithm of pulmonary nodules, the following conclusions can be drawn:

- Wavelet denoising of lung CT images can effectively improve the detection rate and classification accuracy of pulmonary nodules, provide objective decision support for doctors, and ultimately improve the survival rate of lung cancer patients.
- When the number of iterations or the accuracy of the system meets the requirements, the optimal solution of the parameters is input into the CNN structure. The feature extraction of pulmonary nodules in CT images is done through continuous training and learning of the network model. The training efficiency of the convolution neural network optimized by the genetic algorithm is improved, and the error is basically within 0.01%, which can prove the accuracy of the algorithm.
- The convolution neural network optimized by the genetic algorithm is used to detect the pulmonary nodules in the existing CT images of the lung, which can effectively distinguish the characteristics of lung diseases, such as pulmonary hamartoma, pneumonia, and a variety of lung cancer structures.

In this paper [10], a transferable texture CNN architecture for lung nodule malignancy classification tasks was proposed. They introduced the Energy Layer (EL), which removes the overall shape information and explores the texture features. The effectiveness of the proposed technique for benign and malignant nodule classification, without nodule segmentation or any complex pre-processing, was experimentally shown. After successful training, the performance of the proposed network was evaluated by using various evaluation metrics. The results showed that the proposed texture CNN architecture performed well for approximately all the evaluation metrics. The training was done successfully by six-fold cross-validation and achieved an accuracy, recall, specificity, AUC, and error rate of 96.69%, 96.05%, 97.37%, 99.11%, and 3.30%, respectively, on LIDC-IDRI database. The learned features

of EL were analyzed and it was noted that the EL extracted texture from the convolutional layer. The EL also reduced the number of learnable parameters of the network, which leads to minimizing the memory requirements and complexity of CNN. Moreover, the effectiveness of the proposed texture CNN on the MNIST (Modified National Institute of Standards and Technology) dataset was validated and the model achieved 99.89% accuracy with only a 0.12% error rate.

Conclusion

In conclusion, the early detection of lung cancer is critical for improving patient outcomes and survival rates. While traditional methods such as chest X-rays and sputum cytology have been used in the past, they have limitations in terms of sensitivity and specificity, and may not detect small or early-stage tumors. Advancements in imaging technology such as low-dose CT scanning, as well as the development of artificial intelligence-based models have improved the accuracy and speed of lung cancer detection. Dense-Net is a deep-learning architecture that has shown promise in the early detection of malignant lung nodules. Dense-Net has a unique structure which facilitates feature reuse and enhances feature propagation, which has been shown to outperform other deep learning architectures such as Res-Net and U-Net in lung nodule detection. Studies have demonstrated that Dense-Net based models can achieve high accuracy in detecting malignant lung nodules, with sensitivity and specificity values exceeding 90% in some cases. These results suggest that Dense-Net based models have the potential to improve the accuracy and speed of lung cancer detection, which could lead to earlier diagnosis and more effective treatment. Overall, Dense-Net represents a promising approach for the early detection of lung cancer, and ongoing research and development will continue to improve the accuracy and applicability of this technology in clinical settings. However, there are still challenges to be addressed, such as the high false-positive rate of imaging methods and the need for larger and more diverse datasets to train deep learning models. Ongoing research and development of new methods and technologies will continue to improve the ability to detect and treat lung cancer at earlier stages, leading to better patient outcomes and survival rates.

Acknowledgement

I would like to express my deep and sincere gratitude to my project guide, Dr. Kala. L, Associate Professor, NSS College of Engineering, Palakkad, for giving me the opportunity to do research and providing invaluable guidance throughout this research. Her dynamism, vision, sincerity and motivation have deeply inspired me. She has taught me the methodology to carry out the research and to present the research works as clearly as possible. It was a great privilege and honor to work and study under her guidance. I also thank all the staff of Research section of NSS College of Engineering, Palakkad for their kindness. Finally, I would like to thank each and everyone who have supported me to complete the research work successfully.

References

1. Zhou, Jieli, and Hongyi Xin. "Emerging artificial intelligence methods for fighting lung cancer: A survey "Clinical eHealth 5 (2022): 19-34.

2. Chen, Y., Wang, Y., Hu, F., & Wang, D. (2020). A lung-dense deep convolution neural network for robust lung parenchyma segmentation. IEEE Access, 8, 93527-93547.

3. Mukherjee, S., & Bohra, S. U. (2020, December). Lung cancer disease diagnosis using machine learning approach. In 2020 3rd International Conference on Intelligent Sustainable Systems (ICISS) (pp. 207-211). IEEE.

4. Sasikala, S., Bharathi, M., & Sowmiya, B. R. (2018). Lung cancer detection and classification using deep CNN. International Journal of Innovative Technology and Exploring Engineering, 8(25), 259- 262.

5. Zhang, G., Zhang, H., Yao, Y., & Shen, Q. (2022). Attention-Guided Feature Extraction and Multiscale Feature Fusion 3D ResNet for Automated Pulmonary Nodule Detection. IEEE Access, 10, 61530-61543.

6. Liu, Kehong. "STBi-YOLO: A Real-Time Object Detection Method for Lung Nodule Recognition."IEEE Access 10 (2022): 75385-75394.

7. Wang, W., Chakraborty, G., & Chakraborty, B. (2020, December). 3D Multi-scale DenseNet for Malignancy Grade Classification of Pulmonary Nodules. In 2020 11th International Conference on Awareness Science and Technology (iCAST) (pp. 1-4). IEEE.

8. Danku, Alex Ede, et al. "Cancer Diagnosis with the Aid of Artificial Intelligence Modeling Tools."IEEE Access 10 (2022): 20816-20831.

9. Li, G., Zhou, W., Chen, W., Sun, F., Fu, Y., Gong, F., & Zhang, H. (2020). Study on the detection of pulmonary nodules in CT images based on deep learning. IEEE Access, 8, 67300-67309.

10. Ali, I., Muzammil, M., Haq, I. U., Khaliq, A. A., & Abdullah, S. (2020). Efficient lung nodule classification using transferable texture convolutional neural network. IEEE Access, 8, 175859-175870.