

Machine Learning in Diagnosis and Prognosis of Lung Cancer by PET-CT

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Abstract: As a disease with high morbidity and high mortality, lung cancer has seriously harmed people's health. Therefore, early diagnosis and treatment are more important. PET/CT is usually used to obtain the early diagnosis, staging, and curative effect evaluation of tumors, especially lung cancer, due to the heterogeneity of tumors and the differences in artificial image interpretation and other reasons, it also fails to entirely reflect the real situation of tumors. Artificial intelligence (AI) has been applied to all aspects of life. Machine learning (ML) is one of the important ways to realize AI. With the help of the ML method used by PET/CT imaging technology, there are many studies in the diagnosis and treatment of lung cancer. This article summarizes the application progress of ML based on PET/CT in lung cancer, in order to better serve the clinical. In this study, we searched PubMed using machine learning, lung cancer, and PET/CT as keywords to find relevant articles in the past 5 years or more. We found that PET/CT-based ML approaches have achieved significant results in the detection, delineation, classification of pathology, molecular subtyping, staging, and response assessment with survival and prognosis of lung cancer, which can provide clinicians a powerful tool to support and assist in critical daily clinical decisions. However, ML has some shortcomings such as slightly poor repeatability and reliability.

Keywords: machine learning, computed tomography, lung cancer, artificial intelligence, diagnosis

Introduction

Lung cancer remains the primary cause of death around the world.¹ Depending on the histological characteristics of the cancer cells microscopically, lung cancer can be divided into non-small cell lung cancer (NSCLC) and small cell lung cancer (SCLC), with the former accounting for 85%. Common types of NSCLC include squamous cell carcinoma (SCC), adenocarcinoma (ADC), and large cell carcinoma (LCC).² Research shows that^{3,4} the 5-year survival rate after diagnosis of lung cancer is less than 20%, and approximately 62–70% of patients are diagnosed with lung cancer at an advanced stage. The stage of lung malignancies at diagnosis determines its prognosis. In general, the 5-year survival rate of lung cancer in stage I can exceed 80%, but in stage IV, it is close to 0%.⁵ Therefore, early diagnosis and treatment are crucial.⁶ Positron emission tomography and computed tomography with 2-deoxy-2-[fluorine-18]fluoro-D-glucose (¹⁸F-FDG PET/CT, PET/CT for short) is a functional molecular imaging technology. As a non-invasive examination method, it can provide anatomical and functional information of multiple organs and tissues in the whole body, so it has been routinely used for the early identification, staging, and efficacy evaluation of tumors such as lung cancer, rectal cancer, ovarian cancer, breast cancer, and so on, which provides comprehensive diagnosis and treatment information.^{7,8} The most widely used imaging agent for PET/CT examination in clinical practice is ¹⁸F-FDG, which is a glucose analog. By combining the degree of tumor uptake with some semi-quantitative parameters provided by the instrument, it provides most characteristics of the tumor such as size, shape, internal structure, and relationship with surrounding tissues, so it can provide an important reference for tumor treatment and prognosis.⁹ However, due to some special reasons, such as the heterogeneity of the tumor, some characteristics of the tumor which to a certain extent determine the response to treatment and their prognosis information have not been fully displayed according to the current treatment methods.

Meanwhile, the current images are mostly interpreted manually, which is closely related to the experience of doctors. It is sometimes difficult to reach an agreement between different doctors. In addition, if the patient's preparation before imaging is not sufficient or the patients have recently undergone local surgery, radiotherapy, and chemotherapy, false-negative or false-positive results may appear on the PET/CT image.^{10,11} Therefore, more advanced processing methods such as artificial intelligence (AI) are needed to assist in analyzing the imaging information of lesions.

AI refers to the use of computers and advanced technologies to simulate human intelligent behavior and critical thinking,¹² which has achieved great success in research and application.¹³ AI includes many different technologies: intelligent agent,¹⁴ symbolic and subsymbolic reasoning,¹⁵ plan,¹⁶ case-based reasoning,¹⁷ fuzzy systems,¹⁸ expert systems,¹⁹ and so on. The tool that enables most of these techniques is machine learning (ML). ML is a technology that enables machines to imitate human behavior,²⁰ which can generate algorithms from a large number of databases and learn from experience, in other words, by developing some programs and mathematical algorithms that enable computers to program (build models) through experiential learning with or without human intervention, to make predictions and judgments on similar data.²¹ Generally, the more the data, the better the model performance.²² Therefore, ML model training requires powerful data storage and processing capabilities. ML contains four commonly used learning methods,^{23–25} be called reinforcement learning, supervised learning, unsupervised learning, and semi-supervised learning, each of which can be used to solve different tasks. Classic ML methods in practical applications include Support Vector Machines (SVM),²⁶ Random Forest (RF),²⁷ Decision trees (DT),²⁸ Logistic Regression (LR),²⁹ K-nearest neighbors (KNN),³⁰ Naive Bayes (NB), Backpropagation artificial neural network (BP-ANN),³¹ Adaptive boosting (AdaBoost),³² and so on. Most of the algorithms belong to the category of supervised learning. With the rapid growth of science and technology, a new research field has emerged in ML, that is, deep learning (DL). DL, built on top of artificial neural networks, is a complex ML algorithm that mimics how the brain processes information, achieving far better results in speech and image recognition than previous technologies. The common method in DL is the neural network system based on convolution operation called fully convolutional network (FCN), convolutional neural network (CNN), generative adversarial network (GAN), recurrent neural network (RNN), and so on.³³ Among them, CNN has a wide range of applications.^{34–37} It is a convolutional operation and downsampling or pooling operation of artificial neural networks based on depth architecture and multi-layer feedforward neural network, which accepts three-dimensional images as input. It can be trained end-to-end by a supervised method when learning highly discriminative image features. Since convolution operation is mainly used to process data with a grid-like structure, CNN has significant advantages in the analysis and recognition of time series and image data.³⁸

The ML process can be divided into five steps: data acquisition; data preprocessing; model training; model verification and model use, each part of which covers more content and is no longer detailed here. The following words will be used in the practical application of ML, and it is necessary to explain them. The training set is the data used to train the model, the validation set is the data used to optimize the hyperparameters of the model, and the test set is the data used to evaluate the generalization ability of the model. The performance of the general model is evaluated through the confusion matrix, K-S value, AR value, receiver operating characteristic (ROC) curve, and area under curve (AUC). More and more research focus on the application of ML in tumor,^{39–41} but by far, lung cancer is almost the most extensively studied and characterized malignancies.⁴² Many studies have confirmed that PET/CT-based ML can be used for lung tumor recognition, tumor description, diagnosis and differential diagnosis, tumor staging, risk prediction, prognosis assessment, and early role prediction after treatment.^{43–50} Horizontal exploration, such as identification of pathological types, gene mutations, immunohistochemical expression, and prediction of lymph node metastasis. The other category is longitudinal exploration, predicting possible future events, such as efficacy and prognostic predictions. This paper is to summarize the application of PET/CT-based ML methods in lung cancer in recent years (as shown in Figure 1). At present, ¹⁸F-FDG is mostly used as a PET/CT imaging agent. There are few studies on other imaging agents, so the former is generally introduced without special explanation in this paper.

Tumor Detection

Studies⁵¹ have shown that the proportion of malignancy in lung nodules is as high as 6.34%, and the five-year survival rate for early-stage lung cancer with surgical intervention can exceed 90%, so the early and definite diagnosis of lung cancer is of great significance. Although many studies^{52–54} have confirmed the important role of PET/CT in distinguishing benign and

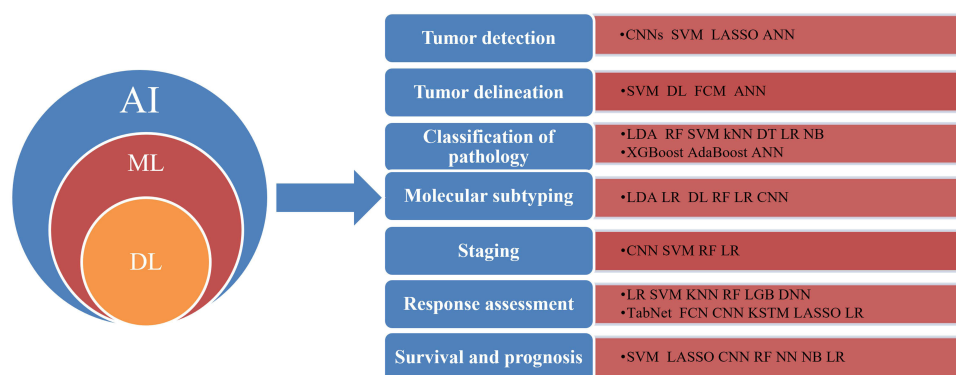


Figure 1 Application of PET/ CT-based ML in lung cancer. The relationship between AI, ML, and DL and the actual use of ML methods in the diagnosis and treatment of lung cancer.

malignant pulmonary nodules, there are some false-positive results such as granulomatous inflammation, organizing pneumonia, or other rare benign lesions, so it is necessary to combine other means to reduce the false-positive rate to avoid over-treatment and waste of medical resources. Therefore, the ML method has been used by many scholars⁵⁵ for the early recognition of carcinoma of the lungs. They have achieved a series of results. For PET-CT research of lung cancer, most of them⁵⁶ obtain diagnostic and radiological features automatically, but they always locate tumors manually. There are few studies^{57,58} that use (ML) to combine automatic segmentation and extraction of lung lesion radiological data. Therefore, some scholars⁵⁹ who used two CNNs, the Detection CNN and Organ CNN to study PET/CT images of lung cancer, found that it could detect 90% of lung cancer and the level of automatic segmentation and extraction data by ML method was close to that of manual extraction, so it is suggested that the future research may be carried out instead of manual work. Another significance of the study was that negative lesions can be screened using the ML method, so clinicians can pay attention to those potentially malignant lesions, which can improve the efficiency of clinical treatment.

The research continues. Some researchers have applied the Least absolute shrinkage and selection operator (LASSO) method on PET/CT images to reduce the false-positive rate in lung malignant tumor diagnosis.⁶⁰ Meanwhile, SVM was also used to analyze the image information of 135 PET/CT patients, and it was found that Surface Volume Ratio and SUV peak had the potential ability to distinguish benign and malignant lung lesions.⁶¹ Some scholars used the dynamic threshold segmentation method to recognize the pulmonary parenchyma in CT images and the suspicious regions in PET images, and then the dubious areas on the CT images were marked using the improved watershed method. Next, SVM was applied to classify pulmonary nodules. Based on the metabolic features of PET images and texture features of CT images, the sensitivity was higher than that of traditional CT methods, reaching 95.6%, and the false-positive rate was low.⁶² Dual-time point imaging (DTPI) can enhance the accuracy of differentiating benign and malignant lesions in PET/CT. In a study,⁶³ SVM modeling was applied to analyze the characteristics of early and delayed PET/CT imaging, which showed higher accuracy and specificity than traditional PET/CT and CT in distinguishing benign and malignant solitary pulmonary nodules (SPNs). Quantitative indicators frequently used in PET/CT in clinical work or research are standard uptake value (SUV max) and metabolically active tumor volume (MTV). However, due to the heterogeneity of tumor shape and uptake, the tumor characteristics cannot be fully described.⁶⁴ In addition, SUV max ≥ 2.5 was used as the diagnostic threshold for malignant SPNs in the past, and the diagnostic efficiency of which was slightly insufficient under some conditions.⁶⁵ Therefore, some studies⁶⁶ have established an SVM model based on texture features to improve the diagnostic evidence of PET/CT in malignant SPNs larger than 5 mL, with an index AUC (95% CI) of 0.854 (0.637–1) which was better than traditional SUV max and MTV metrics. In addition to traditional ML methods, DL also plays a vital role in the early identification of lung malignant tumor. A research⁶⁷ analyzed the information of traditional CT and PET/CT of enrolled cases, established a deep transfer learning (TL) model based on ResNet-18, and found that the performance of the model built using traditional CT was better than that of the CT model in PET/CT. However, data information extracted from PET/CT, including size and SUV max of the pulmonary lesions, can enhance the performance of the DL system and increase the accuracy of PET/CT diagnosis of malignant tumor. CNN also plays a vital role in the

detection of lung tumors, based on a study of 104 PET-CT images of lung nodules. The study found that using CNN reduced the false-positive rate for lung cancer, from 72.8 to 4.9 per case.⁶⁸ Another scholar⁶⁹ used an artificial neural network (ANN) to analyze 18 cases of pure wool glass turbidity on PET/CT images, and compared the ability to explore malignant lesions with that of two blind specialists. It was found that ANN had a good predictive value, the AUC of which was 0.98 ± 0.02 . As we all know, the use of PET/CT imaging is partly subject to its high dose, which is mainly from the radiation emitted by the imaging agent and the CT instrument itself. Therefore, some scholars used the ANN method to perform PET/CT imaging at three scanning doses, namely a standard dose of PET100%, 10% standard PET dose of PET10%, and PET3.3%, to detect lung cancer. The results showed that the AUC at the three doses were 0.989, 0.983, and 0.970, respectively. At the same time, it was found that the sensitivity and specificity of the (ML) method at the standard dose and PET3.3% dose were 95.9% and 91.5%, respectively, and the specificity was 98.1% and 94.2%. Therefore, it was concluded that ML may still be able to better detect lung cancer at lower PET/CT injection dose, which offered a new choice in clinical practice.⁷⁰

Tumor Delineation

After the discovery of the tumor, its accurate description is of great significance for its precision treatment. In recent years, the method of ML has penetrated this field and achieved ideal results. Traditional PET has low spatial resolution and cannot fully describe tumor lesions, so a physics-guided modular DL frame work has been developed for automated tumor segmentation and has been used to accurately characterize primary lung tumors in PET images through small clinical training datasets, which demonstrated the ability to segment small tumors.⁷¹ In other studies,⁷² SVM technology was used to train the outline of gross tumor volumes (GTV) on PET/CT images based on optimal contour selection to distill the initial GTV region. The study found that the 3D dice similarity coefficient (DSC) can reach 0.777, suggesting that this technology can be used as an effective tool to determine tumor GTV.

DL has limitations in the application process, that is, model training requires a large amount of data. To solve this problem, a research team⁷³ integrated the Few Shot Learning (FSL) scheme into the U-Net architecture used for the segmentation of carcinoma of lung lesions on PET/CT scans, permitting dynamic model weight fine-tuning. In addition, an online supervised study plan was created, and the weight of the model was continuously adjusted online according to feedback from users, to increase the accuracy of detection and category, then better detection results were achieved. Through this research, clinicians could more accurately find the size, configuration, and position of the lung cancer and so forth to better serve the clinic.

Radiation therapy (referred to as radiotherapy) is a conventional treatment for lung cancer, and the precise delineation of its target area directly affects its therapeutic effect. PET/CT provides information on the biological activity of the tumor by obtaining the metabolic changes of the tumor, which can be used as an important reference for making radiotherapy plans. However, when PET/CT is routinely used to scan lung tumors, especially lung cancer lesions, due to the influence of respiratory movement, the lung tumors will be slightly displaced, which directly affects the accurate detection of tumors, and then affects the formulation of treatment, especially radiotherapy plans. To reduce the impact of tumor movement, SVM was used to⁷⁴ automatically depict the tumor starting with the first frame. With the help of the level set (LS) deformation model, the dimension and position information of the first was applied to track its movement in succeeding frames, so that the tumor volume of all frames could be accurately depicted, thus planning accurate and effective radiotherapy scope. Another study⁷⁵ included 60 NSCLC patients accepting stereotactic body radiation therapy (SBRT). In this research, PET and CT images of patients were sent to 3D DL fully convolutional networks (DFCN), and a co-segmentation model based upon PET/CT images was established. The study found that the various indicators of model were superior to manual segmentation and models on the strength of PET or CT images individual. Because of the heterogeneity of the tumor, the anatomical and metabolism from PET/CT may not fully reflect the true structure of the tumor. Therefore, studies⁷⁶ have compared three different ML methods fuzzy-c-means clustering method (FCM), ANN, and SVM to establish an automated fralanguage to describe the GTV of lung cancer lesions in PET/CT with stereotactic body radiation therapy. The results showed that various quantitative indicators such as DSC based on the FCM framework were superior to the other two methods, which also provided a method to accurately depict tumors to be more conducive to the formulation of precision radiotherapy plans in the future.



Classification of Pathology

After the tumor is accurately described, the next step is to consider its treatment, but attention must be paid to the subtype of NSCLC before treatment. The most common subtypes of NSCLC are SCC and ADC. It has been reported that different subtypes of NSCLC have different responses to the same treatment.⁷⁷ Therefore, it is important to distinguish NSCLC subtypes before treatment.^{78,79} CT-guided needle biopsy is usually used to diagnose the pathological type, its numerous risks, sampling errors, and non-invasive limit its use. Sometimes this process is achieved with the help of PET/CT, as PET/CT imaging agents vary with different subtypes. However, it is sometimes difficult to distinguish NSCLC subtypes by PET/CT. Therefore, scholars have carried out many studies with the help of ML methods on PET/CT, and a series of results have been achieved in both traditional ML methods and DL, which will be introduced in detail below.

Researchers first explored a linear discriminant analysis (LDA) classifier combined with PET/CT images to distinguish NSCLC subtypes. Because of the small number of enrolled clients in the research, only 30 cases, the conclusions have not been widely considered in clinical practice.⁸⁰ Later, scholars⁸¹ tried to use RF and gradient lift tree models to extract seven kinds of radiomics features extracted from PET/CT images of lung cancer. The results showed that combining image-omics methods was helpful in identifying ADC and SCC. DL methods are also commonly studied and are considered significantly superior to all traditional ML algorithms.⁸²

In addition to using a single ML method for research, some scholars also included multiple ML methods at the same time, trying to find which method is more effective in distinguishing NSCLC subtypes. In this study,⁸³ 1417 patients with NSCLC were enrolled. Ten ML models, such as LDA, SVM, RF, and the VGG16 DL algorithm, were used to extract and analyze PET/CT image features to distinguish the subtypes. It was found that the VGG16 DL algorithm was better than other models. Other scholars⁸⁴ used LR, kNN, DT, and RF to further analyze the PET/CT image characteristics of patients with Phase I and II NSCLC. They found that the model built by kNN and LR had better performance than other methods, because it was in the nonlinear cutting space of kNN, but it had the risk of overfitting, and LR could reduce the risk of overfitting. Both methods were able to distinguish between ADC and SCC. Two different PET/CT scanners were used during the study, so they also found that differences in the instruments could affect the results described above. Shen et al⁸⁵ divided the tumor into multiple subregions according to the tracer metabolism and anatomical structure in PET/CT images. Based on the subregion image and traditional tumor image, seven classifiers were used to build a model to distinguish ADC and SCC. It was found that the performance of the subregion imaging model was superior to that of the tumor region imaging model. The optimal model is SVM with the radial basis function kernel (SVM-RBF) model, with sensitivity, specificity, accuracy, and AUC of 0.8538, 0.8758, 0.8623, and 0.9155, separately.

The clinical characteristics and laboratory indicators of patients play a key role in differentiating ADC from SCC, which can be further enhanced when both are included in ML studies.⁸⁶ Therefore, some scholars⁸⁷ used all kinds of ML learning skills, including LR, LDA, Naive Bayes (NB), KNN, SVM with radial basis function kernel, DT, RF, eXtreme Gradient Boosting (XGBoost), AdaBoost, and ANN combined clinical characteristics and part of laboratory indicators to build model to distinguish the two based on PET/CT radiomics feature. It is found that regardless of the training set or the verification set, the RF model with AUC 0.863 and SVM model with AUC 0.876 have the best diagnostic performance and can better distinguish the two. This study has a better effect than only combining clinical characteristics. Moreover, the study also found that the SVM model is more suitable for small samples, and the RF model is more suitable for situations where there is data loss in the study. Given the difference in glucose metabolism between ADC and SCC,⁸⁸ therefore, researchers⁸⁹ have used a variety of ML methods (RF, neural network, NB, LR, and SVM) to study PET/CT image features of lung cancer. Some clinical characteristics of the subjects, which include age, sex, tumor size, and smoking status, were also introduced. The results indicated that the LR model had better predictive ability than other models (AUC = 0.859, accuracy = 0.769, precision = 0.804) which can distinguish well between pulmonary ADC and SCC. The study also found that Sex, SUV max, gray-level zone length nonuniformity, gray-level nonuniformity for zone, and total lesion glycolysis were the optimum predictors of pulmonary ADC.

Further studies⁹⁰ showed that the prognosis of different ADC subtypes at the same TNM stage may be different, which is determined by the characteristics of histological progression and the main growth pattern. Some scholars tried to use the Dedicaid Automated ML platform combined with PET/CT images of ADC patients and some clinical data, to establish a prediction model for long-term survival outcome and histological features of initially treated ADC patients. In

this study, the 4-year and 3-year tumor grade (TG), overall survival (OS), and histologic growth pattern risk (GPR) of enrolled patients were analyzed. It was found that all parameters responded well, with the highest AUC of 0.88. This study provides a non-invasive means of obtaining ADC subtypes.

Molecular Subtyping

Before treatment of lung cancer, attention should be paid to its efficacy, so we need to find influence factors. Among those factors, one of which is the epidermal growth factor receptor (EGFR) mutation. There are various driver mutations in NSCLC,⁹¹ incorporating oncogenic mutations such as EGFR, BRAF, ROS1, MET, and ALK. EGFR mutations are more common.⁹² If targeted therapy can be carried out for patients with these mutations, compared with traditional chemotherapy, the progression-free survival rate will be increased, and the quality of life will be improved.⁹³ Since the mutation information is usually obtained through invasive means such as surgery or puncture with many side effects, a non-invasive prediction method is needed. Some scholars⁹⁴ tried to extract texture characteristic from CT and PET/CT images of NSCLC patients, with the help of Linear discriminant analysis (LDA) and multivariate LR to establish models. Leave-one-out Cross Validation (LOOCV) was used to validate the model to identify and distinguish EGFR mutation types. The results showed that the model built from PET/CT images had a higher AUC, which may be related to the better tumor segmentation achieved by taking more imaging agents in tumor tissues. However, the tissue surrounding the tumor in CT affected the segmentation. This study has achieved a good prediction effect, which may guide clinical treatment.

Targeted therapy as immune checkpoint inhibitors (ICI) acting on programmed death-1 (PD-1) receptor on T cells or the programmed death ligand-1 (PD-L1) expressed by tumor cells and tyrosine kinase inhibitors (TKI) acting on EGFR are usually used in NSCLC.⁹⁵ However, studies have shown that whether EGFR is mutated or not has different sensitivity to EGFR-TKI treatment,⁹⁶ which plays a vital role in the targeted therapy of NSCLC,⁹⁷ especially related to the efficacy of the treatment.⁹⁸ It is therefore crucial to identify EGFR mutations pretherapy.⁹⁹

The ¹⁸F-labeled small-molecule PET imaging molecular probe ¹⁸F-MPG has been used by some scholars to identify mutated EGFR to screen patients who would benefit from TKI therapy, but as the imaging agents used were too difficult to obtain, it has not been extensively studied.¹⁰⁰ Later, some scholars¹⁰¹ used PET/CT images to establish a DL model, such as small-residual-convolutional neural network (SResCNN) to predict the mutation state of EGFR. EGFR-deep learning score (DLS) was formed to find out which patients could benefit from the two treatments. In this study, the AUC of training, validation, and independent test cohorts were 0.86, 0.83, and 0.81, respectively. At the same time, some researchers used ResNet DL to analyze the PET/CT image features of NSCLC patients in combination with major clinical data, for example, age, gender, and smoking history to build models to predict EGFR mutations whose results are satisfactory. The cases in this study were from multiple centers. The study also pointed out that the combination of patients clinical data was better than the simple analysis of PET/CT image feature modeling in which case prediction sensitivity and accuracy, with AUC ranging from 0.81 to 0.85, sensitivity and accuracy ranging from 0.60 to 0.76 and 0.82 to 0.83, respectively. The “lower-level” prediction models were integrated to the “higher-level” model more effectively by using stacked generalization in the study.¹⁰²

Research on EGFR mutations continues. LASSO was used by some studies in ML to analyze the PET/CT image features of ADC patients, together with some clinical data to create a model to make predictions about the performance of OS in EGFR-positive stage III and IV patients who have previously received systemic therapy. Satisfactory results were achieved.¹⁰³ RF and LR were used to build a prediction model based on PET/CT, and satisfactory results were obtained over the prediction of EGFR mutations. Its AUCs fluctuated from 0.77 to 0.92.¹⁰⁴ Yip¹⁰⁵ et al used MATLAB software and eight PET imaging features to successfully predict EGFR mutation in 348 NSCLC patients and could also predict the prognosis of NSCLC patients after chemotherapy.¹⁰⁶ The above research results avoid non-invasive operations to obtain the information on EGFR mutations, and offer a reference for implementation of EGFR-TKI for the treatment of lung cancer.

More and more studies have proven that for patients with advanced NSCLC, immune blockers targeting PD-1 or PD-L1 can achieve better survival rates than traditional chemotherapy.^{107,108} Therefore, PD-L1 inhibitors have become the standard treatment for some NSCLC patients. PD-L1 is the only clinically approved marker that triggers ICIs therapy, which is usually achieved through invasive procedures. Some studies^{109,110} have found that by using SResCNN to analyze PET/CT imaging and clinical information of NSCLC to build DLS to predict the presentation of PD-L1 in pulmonary malignancy. So it can provide pre-treatment advice for patients who need immunotherapy.



Staging

As we all know, the different stages of the disease are closely related to the prognosis of the neoplasm.¹¹¹ Other things being equal, those who are at the highest risk of lung cancer death benefit the most from early detection,¹¹² and the earlier the stage, the more appropriate treatment, the better the effect. So early identification is more important, providing additional opportunities to provide cure and prevent death from carcinoma of the lungs.¹¹³ PET/CT can be used as a significant imaging technique for clinical staging in lung cancer,¹¹⁴ with the help of ML,^{115–118} its application ability is further improved, which is described below.

Lymph node metastasis is a crucial criterion for clinical staging in lung cancer. Some researchers use PET/CT radiomics to distinguish benign and malignant lymph nodes to help stage lung cancer.¹¹⁹ Other scholars have used different ML and DL means to identify metastasis of mediastinal lymph node in NSCLC patients with PET/CT and achieved ideal results.¹²⁰ At present, CNN is extensively used in the staging of malignant tumor of the lung. The CNN algorithm was used in some studies with PET/CT image data to divide 472 cases into stages T1-T2 or T3-T4. And then cases were included in the training set ($n = 303$), verification set ($n = 75$), together with test set ($n = 94$) teams. The results found that the accuracy rate [correct/(correct + incorrect)] in the training, verification, and test sets was 87%, 86%, and 90%, separately, suggesting the important role of CNN in staging.¹²¹ Other researchers used CNN to predict lymph nodes and distant metastases of NSCLC based on PET/CT, and found that CNN performed well in predicting the N stage, with a prediction accuracy of 0.80.¹²² Therefore, CNN is expected to be used as a staging tool for lung cancer in the immediate future.

People who develop NSCLC with stage I generally have a better prognosis than those with stage II and III.¹²³ Traditional ML research on lung cancer staging often adopts a single method, and the prediction effect varies with a different method. If different ML methods are integrated, the final prediction efficiency will be improved. Therefore, researchers have used the fusion of SVM, RF, and LR to analyze PET/CT image features, and found that the prediction efficiency is higher than that of a single method. By predicting stages II and III of NSCLC, we can identify patients who will benefit from subsequent treatment.¹²⁴

Response Assessment

The choice of tumor treatment is of great significance to its prognosis. Therefore, accurate and reliable decision-making on tumor prognosis can help to plan appropriate treatment programs such as surgery, chemoradiotherapy, targeting, immunotherapy, and so on, and improve patient management according to different stages of the disease.¹²⁵

Sublobar resection was confirmed to be an effective treatment for primary lung cancer, but some studies found that for highly invasive cancer, this resection method could increase the local recurrence rate of lung cancer compared with lobectomy,¹²⁶ therefore, if highly invasive cancer can be identified before surgery, appropriate treatment can be selected. The tumor invasiveness is usually assessed by the tumor diameter and consolidation tumor ratio (CTR) in CT images;¹²⁷ however, CT findings do not completely correspond to pathological findings.¹²⁸ So scholars began to explore new methods. Some experts used ML methods to study PET/CT and CT image data of primary lung cancer undergoing lobectomy or segmentectomy to evaluate the aggressiveness of lung cancer. This study used seven ML methods such as LR, SVM, RF, KNN, light gradient boosting (LGB),¹²⁹ deep neural net (DNN), together with TabNet,¹³⁰ to establish the ensemble model (ENS) individually and jointly. All models performed well, with LR and ENS having better predictive performance than other models. At the same time, the prediction performance of the PET/CT patterns was superior to that of CT.¹³¹

For some lung cancer patients who have lost the chance of surgery, radiotherapy and chemotherapy have become the main means of treatment. If the therapeutic effect can be predicted, the treatment plan can be adjusted in time, and mortality from lung cancer can be reduced. Metabolic tumor volume 50% (MTV50) > 4.04 in PET/CT was found to be a separate predictor of poor prognostic features in NSCLC patients undergoing chemotherapy using ML,¹³² which can be used as a biological marker to predict chemotherapy sensitivity and effectiveness of NSCLC patients. The application of ML in radiotherapy is discussed below. Radiotherapy plans that determine the efficacy rely heavily on image segmentation. Some studies used 3D fully convolutional neural networks (FCN), including CT and PET data, to realize automatic multimodal image segmentation. This method was robust. Its effectiveness was also confirmed by 84 cases of lung cancer.¹³³ U-net, as one of the most favorite image segmentation architectures of CNN, can be used to self-act segment apparatus at risk in radiotherapy for lung cancer. The morphological and metabolic data provided by PET/CT fusion

imaging is utilized to improve the accuracy and radiotherapy effect of lung cancer.^{134–136} SBRT is currently believed to be the criterion treatment for patients with early stage of lung cancer who are medically impractical or refuse surgical operation.¹³⁷ The kernel support tensor machine (KSTM) has been used to predict the prognosis of early NSCLC receiving SBRT. Certain results have been achieved.¹³⁸ Another study using supervised principal component analysis found that mixed PET-CT imaging features improved the prediction of relapse after SBRT treatment.¹³⁹

Immunotherapy is an emerging treatment for lung cancer in recent years. It is a promising approach through immune checkpoint blockade. It has been reported that only a few patients can get great benefit from immunotherapy.¹⁴⁰ Therefore, it is important to predict the outcome of immunotherapy pretherapy. At present, many studies have proven that the neoplasm immune microenvironment (TIME) affects the efficacy of immunotherapy.^{141–144} Therefore, some scholars have used the LASSO logistic regression method to build PET/CT imaging and clinical features such as gender, smoking history, and SUVmax model of NSCLC patients, to reflect TIME phenotypes by predicting the expression of CD8 in tumor tissues to predict the patient's response to immunotherapy.¹⁴⁵ Some results have been obtained.

Survival and Prognosis

Scholars and experts agree^{146,147} that recurrence of NSCLC after comprehensive treatment is an important factor affecting its survival rate, especially within 2 years after curative intent therapy.^{148,149} In the past, recurrence was detected mainly through regular follow-up means, including the detection of tumor markers and imaging examinations such as PET/CT examination, and so on. However, due to the heterogeneity of tumors, the aggressiveness of tumor cells will change during treatment, so the prediction ability of the above means is limited. The mortality rate of NSCLC will reduce if some means, such as ML, can be used to predict recurrence early, so timely treatment is given.^{150–152} The application of ML is not only to process and analyze image data but also to store and record more patient-related information, which can help doctors make personalized medical decisions for patients, understand patients' treatment responses, and predict survival rates. Studies have revealed that the combined application of the CT model and PET model established with ML is better than that applied alone in predicting the local recurrence of NSCLC.^{153,154}

Some scholars¹⁵⁵ used linear SVM to train the PET/CT image features of 30 NSCLC patients and established a new feature set, called size-aware longitudinal pattern (SALoP). After 2 years of follow-up after the last treatment of the patients, it was found to be superior to the traditional radiomic method in predicting prognosis. At the same time, there were also studies¹⁵⁶ using the LASSO program to preprocess PET/CT images, and then utilizing an extracted texture features by the gray-level co-occurrence matrix (GLCM), which was found to be an individual predictor of overall survival of lung cancer. When together with genetic and clinical information, the overall performance of prognostic features was higher.¹⁵⁷ DL has also been studied in this area. Some scholars analyzed pre-treated PET/CT data with the help of CNN and found that it performed well in predicting lung malignant tumor progression and OS. Meanwhile, this study also used a random survival forests (RSF) model based on DL characteristics, which may be associated with meaningful areas and margins of lesions.¹⁵⁸

Single ML has performed well in predicting the recurrence of lung cancer. Therefore, some scholars have tried to use a variety of ML methods to build a prognostic model of lung cancer to determine whether it can help identify factors affecting the development and outcome of tumors, to correctly evaluate the effect of treatment measures.¹⁵⁹ Studies are using six different ML methods: SVM, RF, neural network, naive Bayes, LR, and gradient boosting to analyze the PET/CT imaging features to establish a model for predicting the recurrence of NSCLC after treatment. It was found that the naive Bayes model had the optimum predictive ability, which had an AUC of 0.816. Imaging features such as Gray level size zone matrix-low-intensity short-zone emphasis (GLSZM-LISZE) together with GLSZM-high-intensity zone emphasis (HIZE) extracted from PET/CT were superior to other features in predicting the recurrence of tumors than.¹⁶⁰

In addition to the conventional use of ML to establish predictive models, in recent years, scholars have found that the body composition phenotype may be related to the immune function of the body, thus affecting the therapeutic efficacy and survival of patients.^{161,162} Further studies¹⁶³ have found that the cross-sectional muscle area of the lumbar 3 vertebrae is closely related to the overall muscle mass. Based on the L3 vertebral body level, there were at least three phenotypes of physical compositions, containing visceral fat area (VFA), subcutaneous fat area (SFA), together with skeletal muscle index (SMI) are associated with the prognosis of NSCLC patients.^{164–166} Based on the above research, some scholars¹⁶⁷ used the least absolute shrinkage and selection operator (LASSO) with ten-fold cross-validation methods for the purpose of obtaining state

IV NSCLC baseline PET/CT imaging features, to establish a comprehensive prediction model by combining the above three body component features to get prognostic prediction of patients with advanced NSCLC. They found that the combined prediction model improved the ability to predict progression-free survival in patients with NSCLC in IV stage possessing AUC values of 0.803 and 0.866 in the training and validation sets, separately, compared with the body phenotype or imaging omics prediction models alone.

Conclusions

The data cited in this review mainly came from the following sources: searches of common databases such as PubMed, Medline (Ovid), EMBASE, Google Scholar, and the Cochrane Library on related topics; some research centers, and projects such as cancer screening programs. Multicentric Italian Lung Detection (MILD) trial, a single center in the inflammatory-endemic region, Yale Cancer Center, Princess Margaret Cancer Centre, Veterans Health Service Medical Center, VU University Medical Center, the Cancer Genome Atlas (TCGA) cohort, and American College of Radiology Imaging Network (ACRIN) 6668/Radiation Therapy Oncology Group (RTOG) 0235; institutional databases such as government datasets, Lung Image Database Consortium (LIDC) database, Lung-PET-CT-Dx open dataset from The Cancer Imaging Archive Database (TCIA), the Kaiser Permanente Southern California (KPSC) Cancer Registry and Research Data Warehouse, institutional lung cancer database, public repositories, and local medical institutions. Some of these studies and clinical trials experienced one, two, or even 10 years.

Despite the increasing use of ML in the diagnosis and treatment of lung cancer, there are still some shortcomings. First, interpretability is a challenge in ML applications. An important reason for this is that most ML models do not explicitly identify causal features and simply rely on correlating input features with outcomes, which can lead to unexpected outcomes and uncertain behavior. High-risk medical decisions, such as diagnosis, treatment, and prognostic choices, require interpretable decision-making processes. There is limited interpretability in most ML models, meaning it is difficult to understand how millions of parameters work simultaneously. If clinicians cannot explain how a technique reached a certain conclusion, patients may not have the confidence to accept the results of ML. The second problem is the repeatability of the model. A single dataset was used by most studies for model development and validation, which has a certain degree of bias, and the conclusions may not be applicable to all cases. DL, in particular, is limited by the amount and quality of data used to train the model. Last but not least, many doctors are afraid that their jobs will be replaced by ML, so they are unwilling to accept or even reject this technology from the heart, which hinders the application of ML in clinical practice. From the perspective of the imaging physician, this development should not be seen as a threat, but rather as an opportunity to play a pioneering role in the health care sector and actively shape this transformation process. Machines do not have the ability to have such complex conversations as humans, and the empathy to match that of doctors, which remains an important aspect of the doctor's role.

In the future, clinicians in particular will need to shift their thinking to embrace ML technology, familiarize them with the basic concepts and metrics, increase collaboration with developers and help develop it to meet appropriate clinical needs, who adapt their daily practices to ensure ML works in company with them which is not a threat to their role. At the same time, we actively develop and integrate databases, improve existing ML algorithms and create new ML algorithms, establish comprehensive quality control and standardization tools, data sharing and verification of multi-institutional data to standardize their processes, in order to achieve more efficient and accurate diagnosis, to realize the important role of ML in the diagnosis and treatment of tumors.

Abbreviations

NSCLC, non-small cell lung cancer; SCLC, small cell lung cancer; SCC, squamous cell carcinoma; ADC, adenocarcinoma; large cell carcinoma, LCC; AI, artificial intelligence; SVM, Support Vector Machines; RF, Random Forest; DT, Decision trees; LR, Logistic Regression; KNN, K-nearest neighbors; NB, Naive Bayes; BP-ANN, Backpropagation artificial neural network; AdaBoost, Adaptive boosting; FCN, fully convolutional network; CNN, convolutional neural network; GAN, generative adversarial network; RNN, recurrent neural network; ROC, receiver operating characteristic; AUC, area under the curve; MTV, tumor volume; GTV, gross tumor volumes; FSL, Few Shot Learning; LS, level set; SBRT, stereotactic body radiation therapy; LDA, linear discriminant analysis; NB, Naive Bayes; GPR, growth pattern

risk; EGFR, epidermal growth factor receptor; LOOCV, Leave-one-out Cross Validation; TKI, tyrosine kinase inhibitors; CTR, consolidation tumor ratio; RSF, random survival forests; GLSZM-LISZE, Gray level size zone matrix-low-intensity short-zone emphasis; VFA, containing visceral fat area; SFA, subcutaneous fat area; SMI, skeletal muscle index.

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Disclosure

The authors report no conflicts of interest in this work.

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