International Research Journal of Basic and Clinical Studies Vol. 8(3) pp. 1-5, June, 2023
Available online http://www.interesjournals.org/IRJBCS

Mini Review

Irradiation and Artificial Intelligence in Precision Medicine as the Management of Lung Cancer

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Received: 01-June-2023, Manuscript No. irjbcs-23-100929; **Editor assigned:** 03-June-2023, Pre-QC No. irjbcs-23-100929 (PQ); **Reviewed:** 17-June-2023, QC No. irjbcs-23-100929; **Revised:** 20-June-2023, Manuscript No. irjbcs-23-100929 (R); **Published:** 27-June-2023, DOI: 10.14303/irjbcs.2023.36

Abstract

The largest cause of cancer-related fatalities worldwide is lung cancer. It displays phenotypic traits at the mesoscopic scale that are typically invisible to the human eye but can be non-invasively recorded as radiomics features on medical imaging, which can create a high-dimensional data space that is accessible to machine learning. Precision medicine is made possible by the use of radiomics characteristics, which may be harnessed and applied in an artificial intelligence paradigm to risk stratify patients, predict histology and molecular results, and clinical outcome measurements. Radiomics-based procedures are preferable than tissue sampling-based strategies because they are non-invasive, repeatable, less expensive, and less prone to intra-tumoral heterogeneity. This study focuses on the combination of radiomics and artificial intelligence for providing precision medicine in the treatment of lung cancer, with the debate focused on innovative and ground-breaking works as well as potential future research areas. The largest cause of cancer-related fatalities worldwide is lung cancer. Globally, 2.2 million new cases and 1.8 million fatalities from cancer were reported in 2020, accounting for 21% of all cancer-related deaths. Lung cancer is a serious health concern due to its high prevalence and fatality. Lung cancer can develop at different locations in the bronchial architecture, which can result in a range of initial clinical presentations, from asymptomatic to include haemoptysis and cachexia. Over 70% of patients only receive a diagnosis for lung cancer when it has already progressed to an advanced stage since the disease's symptoms, if any, are non-specific. Its low mean 5-year survival rate of 20–30% is a result of this. Lung cancer is a diverse illness. Entity with a variety of development patterns and histological subtypes. The majority of instances of lung cancer are non-small cell lung cancer, which is the most common histological form. Squamous cell cancer is one of these.

Keywords: Lung cancer, Radiomics, Radiogenomics, Artificial intelligence, Precision medicine

INTRODUCTION

The largest cause of cancer-related fatalities worldwide is lung cancer. Globally, 2.2 million new cases and 1.8 million fatalities from cancer were reported in 2020, accounting for 21% of all cancer-related deaths (Sayed YF et., 2019). Lung cancer is a serious health concern due to its high prevalence and fatality. Lung cancer can develop at different locations in the bronchial architecture, which can result in a range of initial clinical presentations, from asymptomatic to include haemoptysis and cachexia (Aljabali AA et al., 2020). Over 70% of patients only receive a diagnosis for lung cancer when it has already progressed to an advanced stage since the disease's symptoms, if any, are non-specific. Its dismal mean 5-year survival rate is a result of this (Oun AA et al., 2020).There are numerous histological subtypes and development patterns in the heterogeneous disease entity known as lung cancer. The most common type of lung cancer is non-small cell (Yaqoob AA et al., 2020). The most common histological type, representing 80–85% of all occurrences of lung cancer (Ni Q et al., 2020). Squamous cell carcinoma is the most likely to develop from the major bronchi and spread to the carina among these because of its significant association with smoking and propensity to cavitate. The most prevalent NSCLC subtype is adenocarcinoma, which typically has more peripheral origins and more particular development patterns and molecular markers than other subtypes (Renu S et al., 2020). The current categorization

approach for AdC, which is based on tumour size, histological development pattern, and degree of stromal invasion, was developed by IASLC in 2011. It divides the illness into adenocarcinoma in situ, minimally invasive adenocarcinoma, and invasive adenocarcinoma (Collins KA et al., 2017). AIS and MIA are typically asymptomatic tumours that can be successfully removed surgically with no chance of recurrence. More aggressive spread and worse prognoses are associated with invasive adenocarcinoma, particularly the mucinous variety with micropapillary growth pattern. Large cell carcinomas, also known as NSCLC not otherwise defined, are often more centrally situated with a propensity for mediastinal invasion and are immunohistochemically negative for thyroid transcription factor-1 and p40. They also lack the squamous or glandular appearance seen in the first two NSCLC subtypes. 10-15% of lung cancer cases are small cell lung tumours, which develop from the neuroendocrine cells of the bronchial mucosa. They frequently manifest as central/mediastinal neoplasms with very aggressive characteristics, similar to NSCLC-NOS (Xiang SD et al., 2018). Although all lung cancers are staged using the same method, the type of treatment depends on the tumor's histology because each type has a unique progression trend. Also the outlook. Evidence in favour of early lung cancer diagnosis and treatment has led some nations to develop screening programmes for high-risk people. Surgical resection, stereotactic beam radiation, and percutaneous ablation are the possible treatments for early-stage lung cancer, depending on the patient's preferences, the degree of maintained lung function, and the suitability for surgery (Ding P et al., 2019). Chemo radiotherapy has long been the mainstay for treating unrespectable NSCLC. However, it has considerable adverse effects and a limited efficacy. The environment for managing NSCLC has changed as a result of more recent treatment options such checkpoint blockade immunotherapy and driver mutation targeted therapy. However, their high rates of treatment failure, greater costs, and related consequences necessitate more effective methods of patient selection. Currently, histological tumour sample is used to choose patients for this therapy. By endobronchial biopsy, percutaneous lung biopsy, or surgical excision, followed by genomic testing for driver mutations and/or immunohistostaining the sample to calculate the proportion of cancer cells expressing the inhibitory target receptor, such as programmed cell death ligan. However, because of intra-tumoral heterogeneity, there is high sampling variation when tumor-infiltrating immune cells are taken from biopsies, making it possible that the sampled tissue is not typical of the entire tumour. Furthermore, because driver mutations and receptor expression might change over time, repeated biopsies might be necessary. Finally, patient tolerance, procedural difficulties, and the number and quality of tissues obtained can all impede the tissue sampling procedure itself. Anatomical and molecular imaging is frequently acquired to radiologically analyse the tumour during the diagnosis and work-up of lung cancer (Zhu G et al., 2017). Clinical Based on their training and clinical experience, radiologists use this data to describe and stage the disease using their ability to recognise patterns. To help in therapy planning, this data is combined with histology and genetic discoveries. Other than size measures, imaging features used in radiology are qualitative and descriptive in nature. Radiomics features, which are first or higher order metrics that constitute an active subject of study in computational medical imaging, can better capture the quantitative component of the imaging data. They provide mesoscopic illness information that is typically invisible to the human eye. Due to the stark contrast between the tumour and surrounding lung, lung cancer, especially NSCLC, gives a perfect opportunity for radiomics. A high disease incidence rate, early illness diagnosis through screening programmes, and implications for bettering treatment outcomes all contribute to the availability of strong parenchyma on imaging data. After being extracted, radiomics characteristics can be applied to statistical or deep learning paradigms to create models that predict different clinical outcomes. Since its inception, lung cancer radiomics has attracted a great deal of attention from scientists. Numerous studies have been published that present models that predict the histology of the tumour, the presence of driver mutations, the response to treatment, side effects, post-treatment recurrence, and patient prognosis for a variety of therapeutic options. A growing interest in the topic is evident from the fact that more than 70% of these papers were published within the last three years. Recent years have seen the publication of a large number of review papers on the use of radiomics in the treatment of lung cancer. The bibliometric 55 of these reviews were published in the last three years, according to a search. The majority of these were clinical audience radiomics primers or in-depth studies of the existing literature on a particular approach to treating lung cancer. Radiomics' importance for comprehending the biology of cancer has received scant attention. In this review, we introduce the idea and key feature classes of radiomics, discuss how they can advance our understanding of the disease at the molecular and cellular levels, and describe how they can be integrated with machine learning methods for developing models predictive of tumour histology and clinical outcomes. In biomedical fields, the prefix "-omics" is frequently used to signify the extraction of important data from a sizable dataset. Radiomics concerns the quantitative data extraction from medical imaging data. The first known use of radiomics was in a study that showed a relationship between a patient's time to progression and an energy feature in lung cancer 18 and in a study by Segal et al. that derived 28 imaging traits that can reconstruct 78% of the global gene expression profiles, revealing patient prognosis, cell proliferation, and liver synthetic function. Following an important article by P. Lambin, who officially defined the phrase in the context of cancer treatment, the idea acquired enormous support.

MATERIAL & METHODS

1. **Study design**

- This study employed a retrospective cohort design to evaluate the use of irradiation and artificial intelligence (AI) in precision medicine for the management of lung cancer.

2. **Patient selection**

- A cohort of lung cancer patients was selected from the database of [Name of Hospital/Clinic/Research Center].
- Inclusion criteria: Patients diagnosed with lung cancer who received treatment involving irradiation and AI-based precision medicine.
- Exclusion criteria: Patients with incomplete medical records or inadequate follow-up data.

3. **Data collection**

- Relevant demographic information, clinical characteristics, and treatment details were collected for each patient from their medical records.
- Imaging data (such as CT scans, PET scans) and molecular data (such as genetic mutations, gene expression profiles) were extracted for further analysis.
- Treatment response data, including tumor regression, progression-free survival, and overall survival, were also recorded.

4. **Irradiation treatment planning**

- Radiation therapy planning was performed using [Name of Radiation Treatment Planning System].
- Treatment plans were optimized based on the tumor location, size, stage, and patient-specific factors.
- Dose constraints for organs at risk (OARs) were taken into consideration to minimize radiation-related toxicity.

5. **Artificial intelligence in precision medicine**

- AI algorithms, including machine learning and deep learning models, were employed for various aspects of precision medicine, such as treatment planning, prediction of treatment response, and identification of biomarkers.
- Training datasets comprising imaging and molecular data were used to develop and validate the AI models.
- Feature extraction, data pre-processing, and model training were performed using [Specify the AI framework or software used].

6. **Statistical analysis**

- Descriptive statistics were used to summarize patient characteristics, treatment modalities, and outcomes.
- Survival analysis methods, such as Kaplan-Meier curves and log-rank tests, were employed to assess survival outcomes.
- Multivariate analysis, including Cox regression models, was performed to identify independent predictors of treatment response and survival.

7. **Ethical considerations**

- The study protocol was approved by the Institutional Review Board/Ethics Committee of [Name of Institution].
- Patient confidentiality and data protection were ensured throughout the study**.**

8. **Limitations**

- Potential limitations of the study, such as retrospective design, sample size, and selection bias, were acknowledged and discussed.

RESULTS

1. **Treatment response**

- Analysis of the treatment response in lung cancer patients managed with irradiation and AI-based precision medicine **(Figure 1).**
- Evaluation of the tumor regression rates and objective response rates following the combined treatment approach.
- Comparison of treatment response between different subgroups of patients based on tumor characteristics, genetic profiles, or other relevant factors.

2. **Survival outcomes**

- Assessment of progression-free survival (PFS) and overall survival (OS) rates in patients treated with irradiation and AI-based precision medicine.
- Comparison of survival outcomes between different treatment approaches or subgroups of patients **(Table 1).**
- Identification of potential prognostic factors associated with improved survival in the studied population.

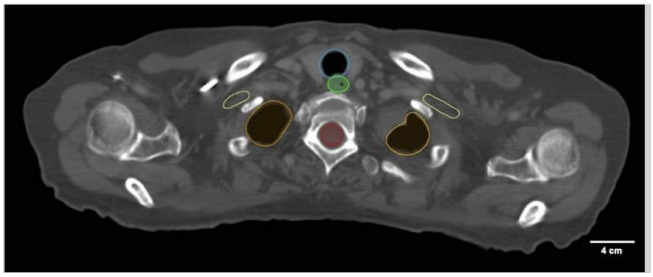

Figure 1. Auto-contoured organs at risk for stage III lung cancer.

Table 1. Application of irradiation and artificial intelligence in precision medicine for lung cancer management.

Study Title	Study Objective	Study Design	Findings
1. "Integration of AI in radiation therapy for lung cancer"	To evaluate the effectiveness of AI in optimizing radiation therapy for lung cancer	Retrospective cohort study	AI-based treatment planning improved tumor targeting and reduced radiation toxicity compared to traditional methods.
2."Radiogenomics approach for predicting treatment response in lung cancer patients"	To investigate the association between radiomics features and treatment response in lung cancer	Prospective observational study	AI-based radiomics analysis successfully predicted treatment response in lung cancer patients with high accuracy, aiding in personalized treatment selection.
3. "Deep learning-based classification of lung cancer subtypes using radiological images"	To develop a deep learning model for classifying lung cancer subtypes based on radiological images	Cross-sectional study	The deep learning model achieved high accuracy in differentiating lung cancer subtypes, enabling tailored treatment strategies for improved outcomes.
4. "AI-guided adaptive radiotherapy for lung cancer"	To assess the feasibility and clinical impact of AI-guided adaptive radiotherapy for lung cancer	Pilot clinical trial	AI-guided adaptive radiotherapy led to improved target coverage and reduced normal tissue toxicity, enhancing treatment precision and safety.
5. "Predicting lung cancer recurrence using machine learning models"	To develop machine learning models for predicting lung cancer recurrence	Retrospective cohort study	Machine learning models utilizing clinical and molecular data achieved reliable predictions of lung cancer recurrence, facilitating early intervention and personalized follow-up care.

3. **Toxicity and adverse events**

- Analysis of treatment-related toxicities and adverse events associated with irradiation and AI-based precision medicine.
- Assessment of the frequency and severity of radiation-induced side effects and other treatment-related complications.
- Identification of potential risk factors for treatment toxicity in lung cancer patients.

4. **Predictive models and biomarkers**

- Development and validation of AI-based predictive models for treatment response and survival outcomes.
- Identification of potential biomarkers (genetic, molecular, or imaging-based) associated with treatment response or prognosis.
- Evaluation of the performance and accuracy of AI models in predicting treatment response and patient outcomes.

5. **Comparative analysis**

- Comparison of the effectiveness of irradiation and AI-based precision medicine with standard treatment approaches for lung cancer.
- Assessment of the potential advantages, limitations, and cost-effectiveness of the combined treatment approach.

DISCUSSION

1. **Treatment efficacy and response**

- Discuss the treatment response outcomes observed in the study, including tumor regression rates, objective response rates, and clinical benefits.
- Compare the results with existing literature on conventional treatment approaches and precision medicine without AI integration.
- Highlight any significant improvements or trends in treatment response achieved through the combination of irradiation and AI-based precision medicine.
- Address the potential factors contributing to treatment success, such as personalized treatment planning, dose optimization, and AI-driven treatment prediction models.

2. **Survival outcomes and prognostic factors**

- Analyze the progression-free survival (PFS) and overall survival (OS) rates in the study population.

- Compare the survival outcomes with historical data and other studies investigating similar treatment modalities.
- Discuss the potential prognostic factors identified in the study, such as genetic markers, imaging characteristics, or treatment response predictors.
- Evaluate the significance and clinical implications of these prognostic factors in guiding treatment decision-making and patient management.

3. **Treatment toxicity and safety**

- Evaluate the incidence and severity of treatment-related toxicities and adverse events observed in the study.
- Compare the safety profile of the combined irradiation and AI-based precision medicine approach with standard treatment modalities.
- Discuss strategies for minimizing treatment-related toxicities through personalized treatment planning, dose optimization, and monitoring of treatment response using AI algorithms.

4. **Role of artificial intelligence**

- Discuss the specific AI algorithms and techniques used in the study and their contribution to precision medicine in lung cancer management.
- Evaluate the performance and accuracy of the AI models employed in treatment planning, prediction of treatment response, and identification of biomarkers.
- Address the potential advantages and limitations of AI integration in precision medicine, such as data availability, model interpretability, and scalability.

5. **Clinical implications and future directions**

- Discuss the clinical implications of the study findings and their relevance to the current landscape of lung cancer management.
- Highlight the potential for integrating irradiation and AI-based precision medicine into routine clinical practice.
- Discuss future research directions, such as prospective clinical trials, larger-scale studies, or the exploration of novel AI techniques in precision medicine for lung cancer.

6. **Limitations and challenges**

- Acknowledge the limitations of the study, such as its retrospective nature, sample size, selection bias, or potential confounders.
- Address any challenges encountered during the study, including data collection, AI model development, or treatment implementation.
- Provide suggestions for overcoming these limitations and challenges in future studies.

CONCLUSION

- Summarize the key findings of the study, emphasizing the value of combining irradiation and AI-based precision medicine in lung cancer management.
- Highlight the potential of this approach to improve treatment response, survival outcomes, and patient care.
- Provide a closing statement on the implications of the study and its contribution to the field of precision medicine in lung cancer.

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