Integration of artificial intelligence in lung cancer: Rise of the machine

Presenter: Ningyuan Xiong

Introduction

- Focus: Oncology and Lung Cancer Management
- Goal of the study:
    - Summarize the current literature in AI specific to **lung cancer**.
    - How it applies to the multidisciplinary team taking care of complex patients.

INTRODUCTION

- Context & Importance of AI in Lung Cancer Management
  - **Barrier**: Large amount of data are difficult to filter and interpret.
  - **AI in demand:** Help Streamlining the increasingly vast amount of clinical data to help guide oncologists in the management of their patients.

- Lung Cancer Management
    - Personalized treatment
    - Multiple stage & diverse data types

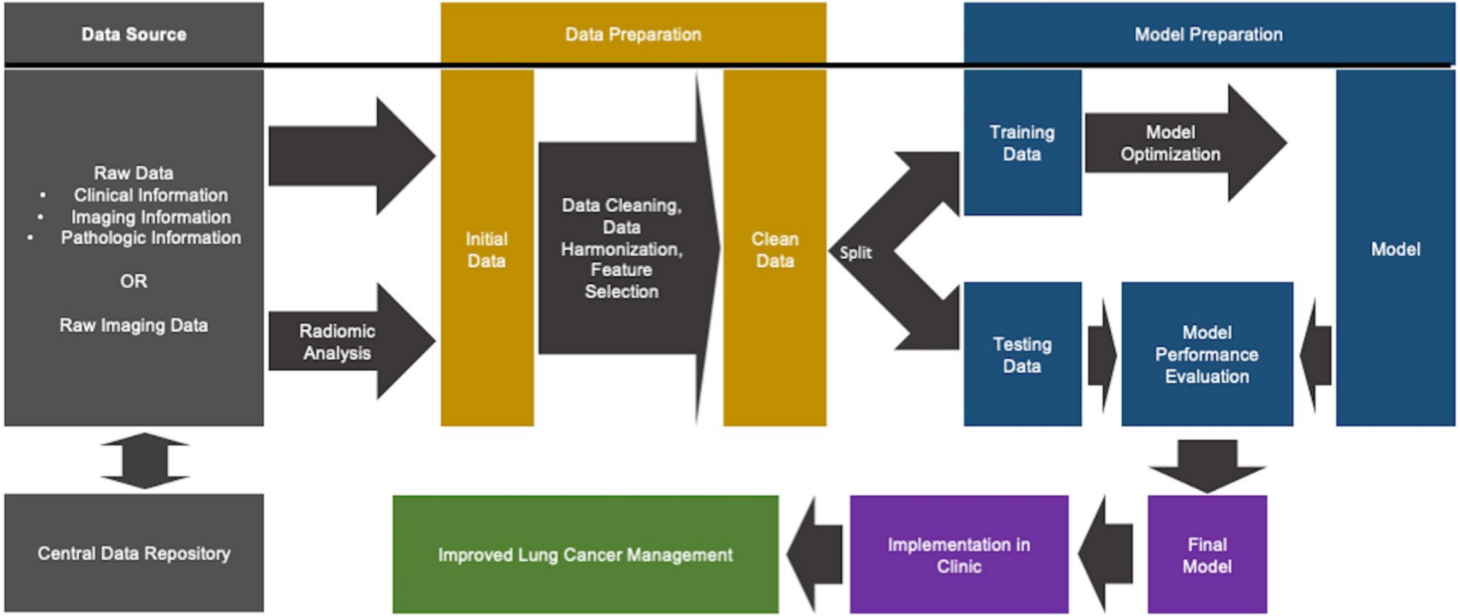


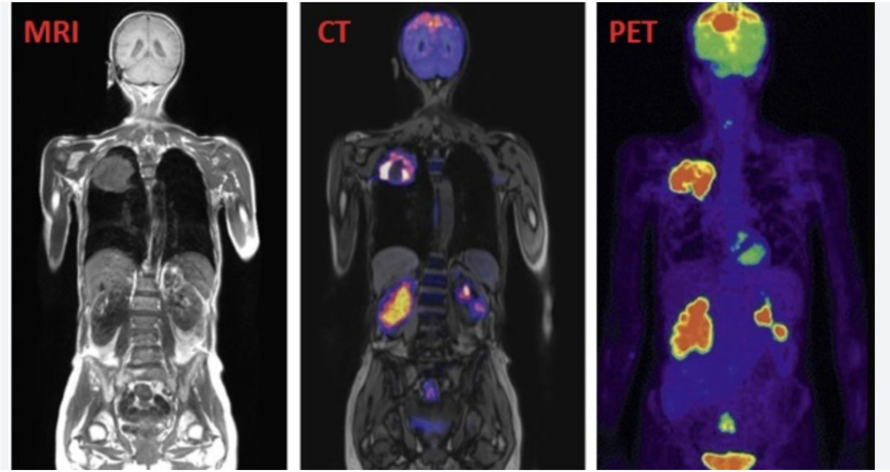
Figure 1. Clinical AI workflow schema
Simplified schema of workflow for implementation of AI in lung cancer clinic on the basis of artificial intelligence best practices.

AI DATA SOURCES

- Data Sources:
  - **Electrical Medical Record (EMR)**
- Challenges:
  - **Harmonization**
  - **Patient Privacy**
  - **Querying**
- Applications:
  - **Risk Identification:** XGBoost with AUC of 0.88
  - **Cancer Progression:** NLP prediction model with AUC of 0.77

DIAGNOSTIC MODALITIES

- **Imaging:**
  - Magnetic Resonance Imaging (MRI)
  - Computed Tomography (CT)
  - Positron Emission Tomography (PET)
- **AI augments imaging:**



CAD system	**Radiomics**	**CNNs**
Computer-aided detection & diagnosis	Data-characterization algorithms with large size feature data	Convolutional neural networks
Binary outcomes	High-dimensional data	Direct image inputs

DIAGNOSTIC MODALITIES

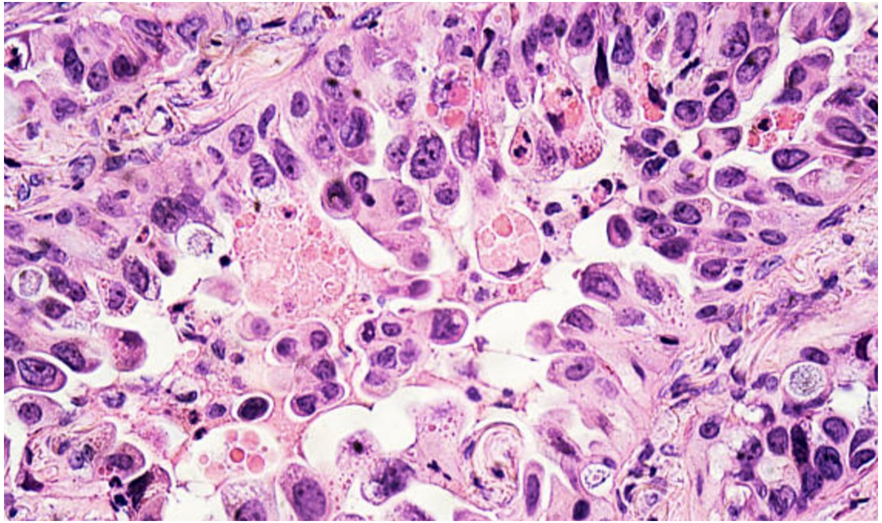
Screening:

- **Challenges:**
  - Low specificity in current screening methods
  - Indeterminate nodules with over 90% not malignant
  - No guideline in classifying small indeterminate nodules as benign or malignant
- **AI Application:**
  - CAD systems have been applied to identify nodules on CT imaging
    - **Computer-aided detection (CADe) Systems: Detecting the presence and location of lesions**
    - **Computer-aided diagnosis (CADx) Systems: Characterize lesions, including identify if it is malignant**
  - CNNs have been used to classify nodules and achieved high AUC.

DIAGNOSTIC MODALITIES

- **Outcome Prediction:**
  - **Complexity of Cancer**: Cancer is a highly complex disease
  - **Subjectivity:** Traditional methods only uses tumor size in its staging algorithm
  - **Multivariate Factors:** Factors like **locoregional recurrence**, **progression-free survival,** and **overall survival** need to be considered
- **How AI is used:**
  - Extract quantitative features from medical images, creating a rich data set for analysis
  - Combined radiomic features with other data types to create more accurate models

Pathology



Histologic classification:

1. **CNN:**
   - Applied for tumor characterization.
   - Classify histology samples with AUC of 0.97.
   - Predict gene mutations with AUC 0.73–0.86.
2. **Immunohistochemistry**
   - Critical for subtyping of non-small-cell lung cancer (NSCLC)
   - Difficult to perform when there is limited tissue available
   - Achieved high accuracy (72.2%-91.7%) using **decision tree** and **SVM** classifiers for subtyping

Pathology

Analysis of Liquid Biopsies

1. **Utility**

- Liquid biopsies can capture temporal heterogeneity.
- Useful for early-stage disease and monitoring progression.

2. **Techniques**

- **Synthetic minority oversampling (SMOTE)** with **random forests** achieving AUC of 0.99.

Genetic Mutations and Gene Expression

- Identify actionable biomarkers
- Understanding genomic pathways

Medical oncology

- **Major Challenge in Drug Discovery:**
  - Optimization of drug development
  - In-silico drug screening
- **AI:**
  - Screen previously developed drugs for new uses
  - Help identify potential drug candidates worthy of further investigation
- **Example study:**
  - Deep Learning algorithm was used to identify that pimozide could be a candidate for Non-Small Cell Lung Cancer (NSCLC).

Radiation oncology

Treatment planning:

- Multiple complex steps:
  - CT simulation
  - Delineation of organs at risk (OARs)
  - Definition of target volumes
  - Treatment plan optimization
  - …

Example study:

- Automatically contouring OARs in CT images
- Automated planning algorithm
- Machine learning to predict quality assurance metrics, using a SVM to minimize errors in the optimization process

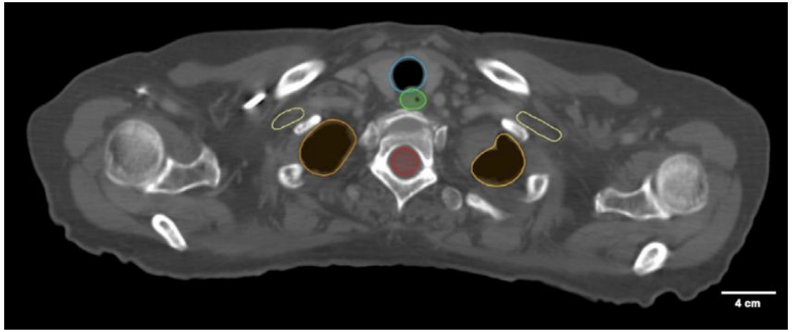


Figure 3. Examples of auto-contoured organs at risk for stage III lung cancer

Radiation oncology

Treatment Selection:

- The use of postoperative radiotherapy (PORT) in certain lung cancer cases is debated
- XGBoost model helps to identify patients who could still benefit from PORT based on factors like nodal burden
- Outperformed traditional methods like Cox regression

Surgery

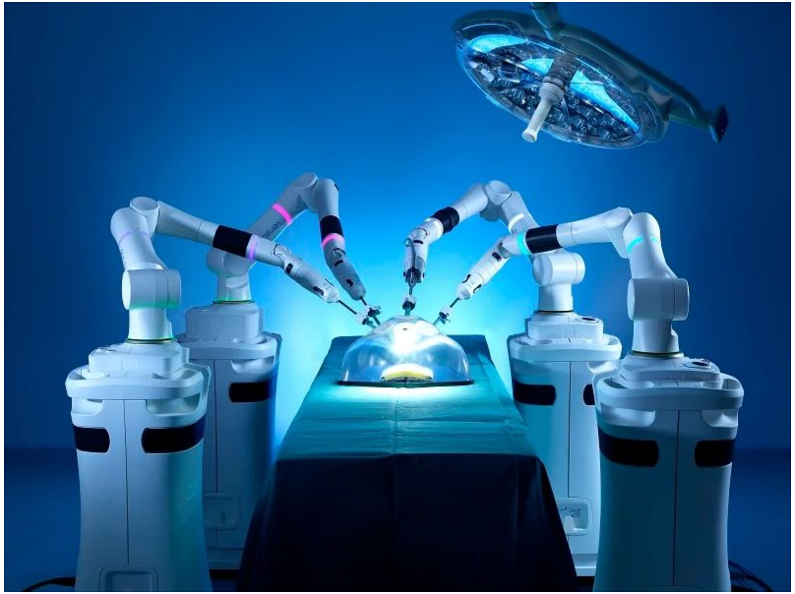
Challenge for Lobectomy:

- Not every patient will be a candidate

AI in decision making:

- Risk Stratification
- Postoperative Prognosis
- Pulmonary Function Tests

Surgery



AI in Robotic surgery:

- **Precision and Minimally Invasive:**
  - Allow for greater surgical precision
  - Less trauma for the patient
- **Automated Planning:**
  - Smart autonomous robots like the STAR system
  - Perform repetitive tasks more efficiently than humans
  - Not yet approved for human clinical care

CURRENT CHALLENGES

- **Data Limitations:** AI requires large, well-organized datasets.
- **Reproducibility:** Varying methodologies make it difficult to replicate studies.
- **Lack of Clinical Application:** Most research is focused on data analysis rather than real-world, patient-focused applications.
- **Ethical Concerns:** Issues around patient consent, confidentiality, and data use for decision-making by AI tools need to be addressed.
- **Complexity:** AI models can be complex and difficult for clinicians to understand, affecting their adoption.

Quiz 1

Screening: Which of the following best describes the primary function of Computer-Aided Detection (CAD) systems in the context of lung cancer screening using low-dose CT scans?

A) Characterizing the malignancy of detected nodules

B) Detecting the presence and location of lesions

C) Predicting patient outcomes based on nodules detected

D) Identifying the genomic features of the cancer

Quiz 2

Outcome Prediction: What is one of the main challenges in predicting oncologic outcomes like survival or recurrence based solely on traditional staging methods?

A) They are computationally expensive

B) They often miss small nodules

C) They may not accurately capture the multivariate factors affecting the outcome

D) They are prone to overfitting

Q&A

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Thank you