InferVision AI Research platform – *InferScholar™*

Empower Medical Research with Deep Learning and Radiomics

Medical Research in the Era of Big Data

Recently, big data analysis has started to play a critical role in clinical research and practice. With the ever-evolving technologies of information science, many hospitals have accomplished medical data digitalization, which is the foundation for further development of big data research.

Big data, by definition, is not only data in large amounts, but also data possessing high dimensionality. For example, to tell whether patients have bone fractures from 1000 cases using X-ray images, big data analysis has to discover the relationship between the 3000 X 3000 pixels of all 1000 images and the pixel properties of fractures. Because of high dimensionality of the data (3000 X 3000 characteristic variables, which is far beyond the total sample amount of 1000), conventional statistical models, such as linear regression, cannot handle such challenges. High dimensionality is usually seen in medical data and datasets such as medical imaging, electronic medical records, and gene sequencing are all high dimensional.

Though the analysis cannot be handled by conventional statistical methods, deep learning provides advanced solutions. Since the ImageNet competition in 2012, deep learning has become the primary method for non-structural big data (such as image, voice and big text) analysis.

In the last 2 years, articles featuring deep learning methodology have frequently appeared in world-renowned journals. To name a few; an article by Google using machine learning to recognize diabetes-related retinopathy was published in ***JAMA*** in 2016; work from a Stanford team using deep learning to categorize skin cancer was published as a cover article in ***Nature*** in 2017; and an article combining China's doctors' work was published as the cover in ***Cell*** in 2018, demonstrating an AI system able to diagnose eye diseases and pneumonia based on deep learning. According to Litjens *et. al.*, from 2012 to 2016, over 300 articles about deep learning related to medical imaging research have been published in journals and conferences, and the number has been increasing exponentially (Figure 1). The methodology of deep learning has also been applied to the analysis of X-ray, CT, MRI, pathology, electronic medical records, endoscopy and other medical big data formats; involving lesion positions in the brain, chest, abdomen, cardiovascular system and bones.

The concept of radiomics was first proposed in 2012 by Dutch scientists. By using automated algorithms, radiomics first obtains large amounts of feature information from the region of interests of medical images as the research target, then extracts the critical information from the information using statistical analysis or data mining methods (such as classical machine learning techniques including supporting vector machine, decision tree and Bayesian algorithms), which is finally used for auxiliary diagnosis, prognosis and treatment monitoring.

The pipeline of radiomics can be summarized in the following steps: (1) imaging data collection, (2) region of interest segmentation, (3) feature extraction, (4) classification and prediction.

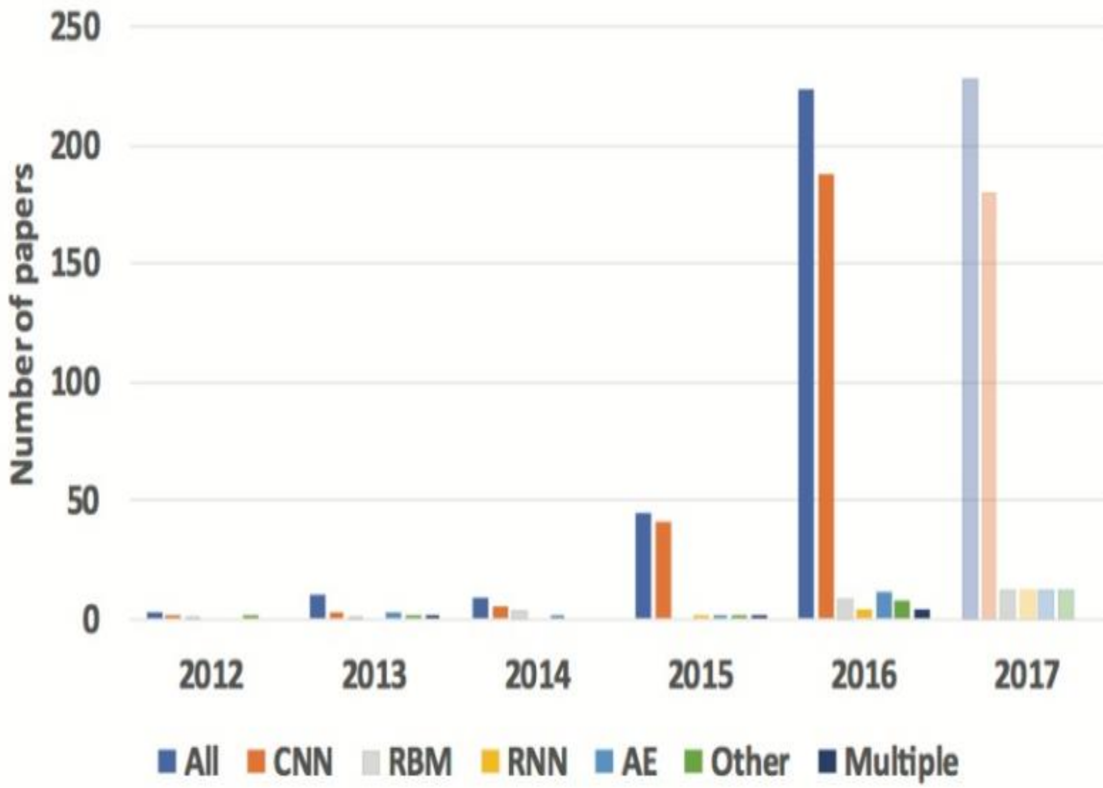


Figure 1. Number of publications of medical imaging research based on deep learning.

A Brief Introduction to InferScholar™

Solid programming ability and integrative knowledge of math, statistics and computer science are usually required for scholars to be engaged in deep learning and radiomics related research. However, accumulation of such interdisciplinary knowledge typically requests long term and systematical academic training, which limits the propagation and application of deep learning in different academic areas. Specifically, it limits the application of radiomics in medical imaging related research in the era of big data.

The InferVision AI scholar platform *InferScholar* (Figure 2) provides a convenient visualizable big data analysis tool for medical researchers. By integrating advanced and multiple deep learning radiomics algorithms, it converts the modeling and programming into simplified interfaces, which enables the medical researchers who are not familiar with computer programming the ability to launch deep learning and radiomics related research.

With the core concept of "empowering medical research with deep learning and radiomics", InferScholar aims to promote the methodology of deep learning and radiomics in medical imaging research.

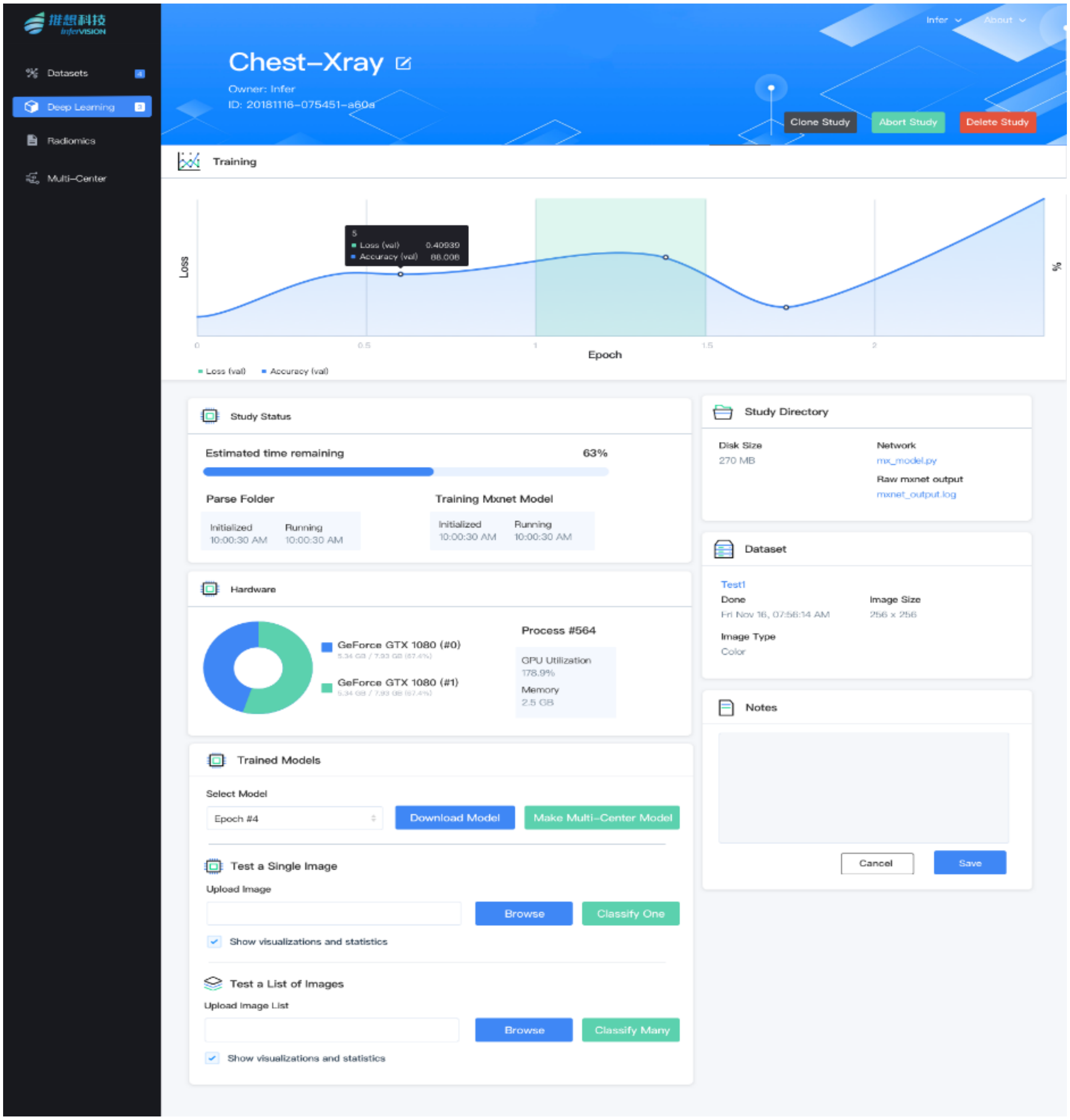


Figure 2. InferVision AI research platform *InferScholar™*

InferScholar Functional Modules

InferScholar integrates high performance deep learning computing servers, intelligence databases, labeling tools, deep learning modeling systems, intelligence radiomics, deep learning training courses and customized deep learning research services to empower hospitals to launch advanced deep learning and radiomics research; enabling them to foster a new generation of medical researchers with interdisciplinary research abilities.

InferScholar Computation Server

InferScholar's computing server adopts the leading Pascal GPU architecture, which is equivalent to hundreds of x86 servers and can complete tasks that would take conventional computing platforms over thousands of hours within 1 hour.

1. The InferScholar server stack includes a deep learning framework, an NVIDIA GPU training system, a deep learning SDK, an NVIDIA Docker, GPU drivers and CUDA, which can be used to design and evolve deep neural networks quickly.
2. The adoption of a CUDA parallel computing platform significantly improves the efficiency of deep learning algorithms.
3. This architecture is particularly good at handling parallel workloads, speeding up the evolving of neural networks by 10 – 20 times and is more quiet than conventional servers.
4. With the integration of CoWoS techniques adopting HBM2 interface, RAM performance is improved by over 300%.
5. Infervision's unique page migration engine makes InferScholar more optimized for computation, reducing efforts in data management.
6. InferScholar adopts the most advanced architecture from NVIDIA, which greatly improves performance and power efficiency.

InferScholar Intelligence Database

The InferScholar intelligence database (Figure 3) includes document management, DICOM information documentation and storage, work list control, labeling information storage, information statistics, information inquiry and monitoring, user management and log on controls. It integrates applicable programs and practical tools for medical institutions and the core function utilizes DICOM standards. It supports CT, MR, X-ray, mammography and other imaging modalities, with abundant and versatile functions. This product also provides storage and inquiry services for medical imaging situations.

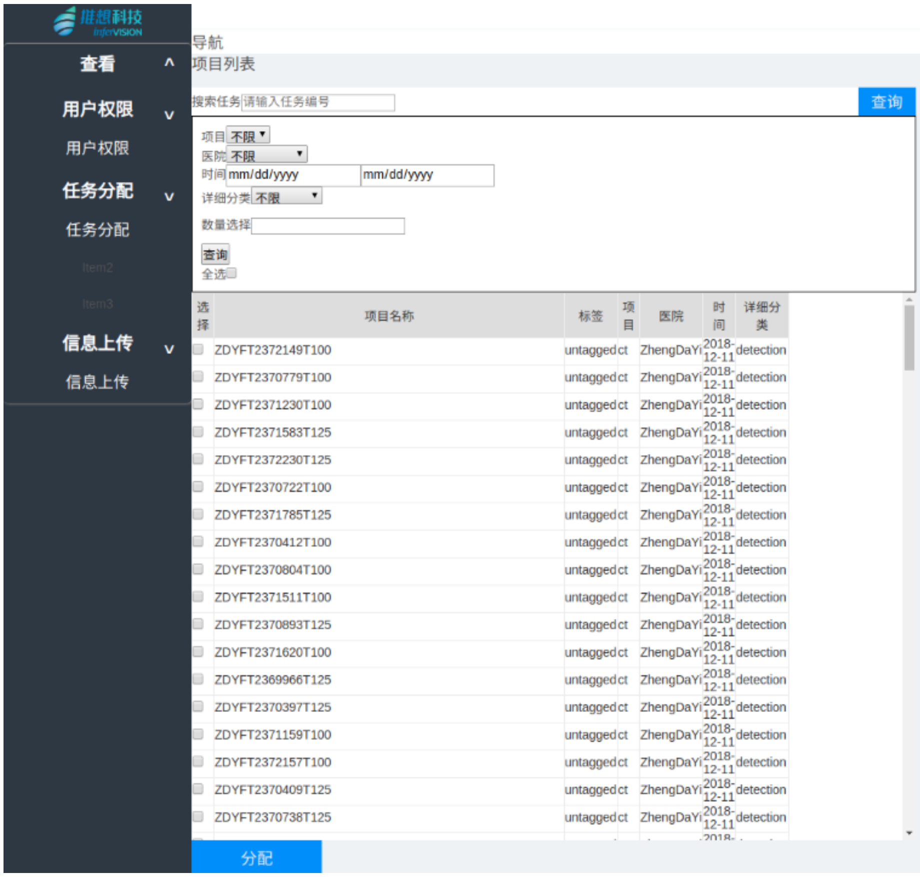


Figure 3. Intelligence Database.

InferScholar Intelligence Labeling Tools

Supervised learning is currently the most mature deep learning technique. For supervised learning, the model training and radiomics feature extractions are both dependent on the labeled data. This module provides standardized, convenient and directly-visualizable labelling systems for categorization, image segmentation, detection and radiomics analysis (Figure 4 & 5). Currently, the labeling tools can be used for:

- MR imaging lesion classification
- MR imaging lesion detection
- MR imaging segmentation
- CT imaging lesion classification
- CT imaging lesion detection
- CT imaging segmentation
- X-ray imaging lesion classification
- X-ray imaging lesion detection
- X-ray imaging segmentation
- Mammography lesion classification
- Mammography lesion detection
- Mammography segmentation
- Other DICOM imaging labeling tools can be customized according to needs

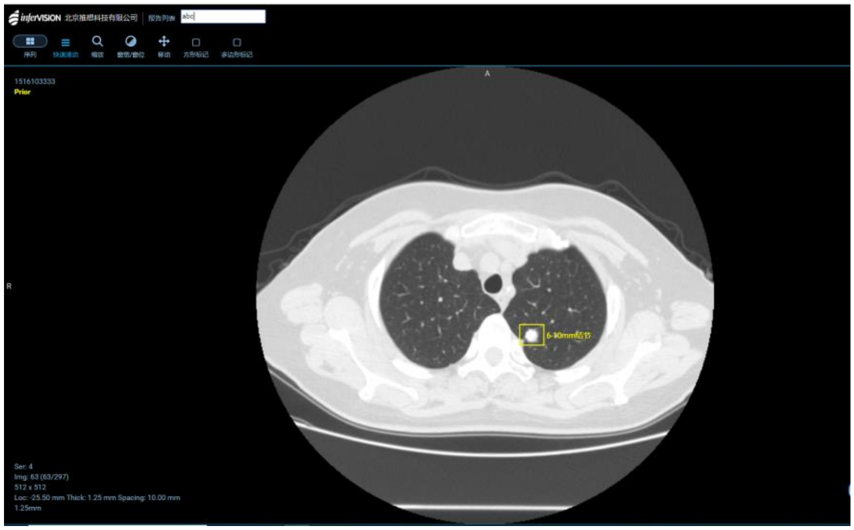


Figure 4. InferScholar's CT intelligence detection labeling tool.

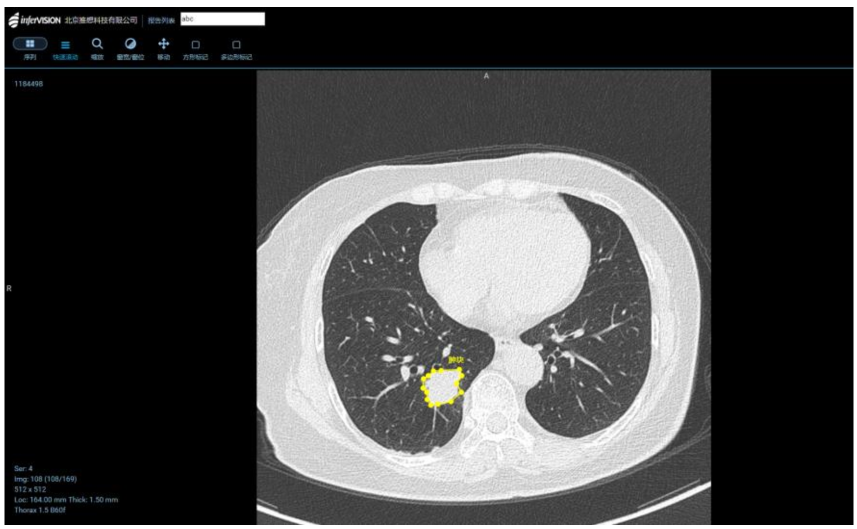


Figure 5. InferScholar's CT intelligence segmentation tool

InferScholar Deep Learning Modeling System

Based on the institution's medical imaging research goal, related projects can be categorized as classification, detection and segmentation; which are all closely related with diagnosis. Classification is usually the first question to be answered by deep learning; that is, with the input of the whole or part of the medical images, the computer will provide a single binary output telling whether lesions exists. Then, target or lesion detection are the next critical steps during diagnosis, which is typically the most effort-consuming step for radiologists. Finally, segmentation is important to precisely determine the target contour, shape and volume, which is also key in clinical practice.

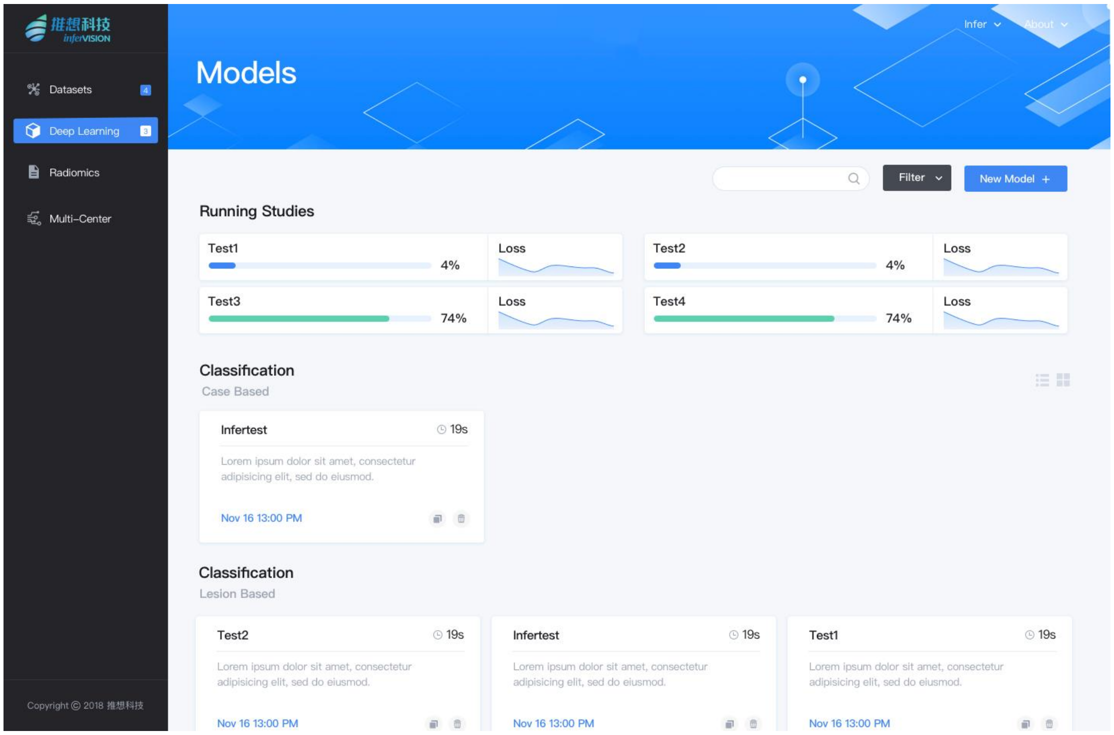


Figure 6. InferScholar's intelligence modeling system interface.

The InferScholar modeling system integrates various classic and up-to-date deep learning algorithms, including:

- For classification: ResNet, Inception, DenseNet, etc.
- For detection: Faster-RCNN, SSD, YOLO, etc.
- For segmentation: Mask-RCNN, UNet, Deeplab, etc.
- The systems also supports customized model design, import and export.

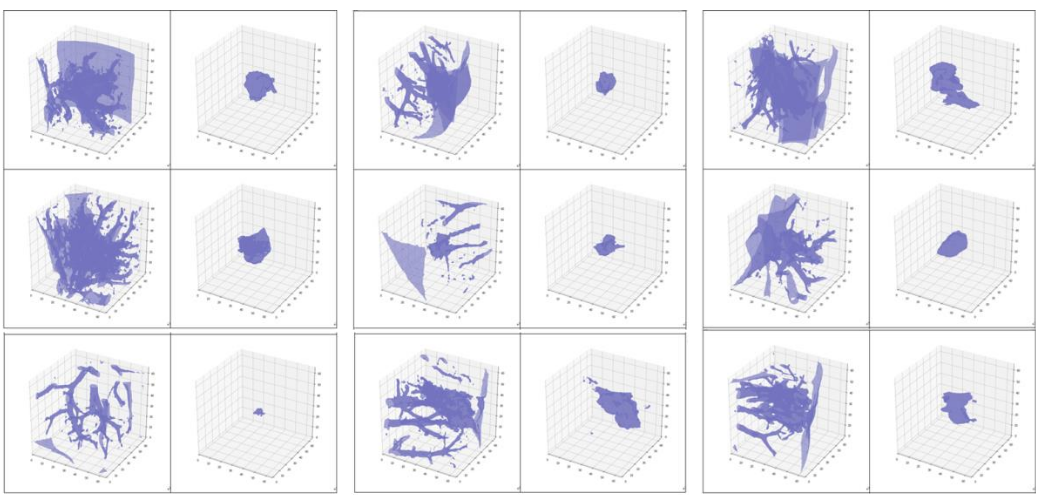


Figure 7. Pulmonary nodule and the surrounding tissues segmented by InferScholar.

The modeling system is specifically tuned based on conventional 2D and 3D images, making it suitable for 2D medical images such as X-ray and mammograph, and 3D modalities such as CT and MRI.

Tunable model parameters include:

- Training epochs
- Callbacks
- Validation interval
- Batch size
- Random seed
- Learning rate
- Optimization methods
- Data preprocessing
- Pretrained parameters
- Data encoding
- Data transformation
- Data augmentation

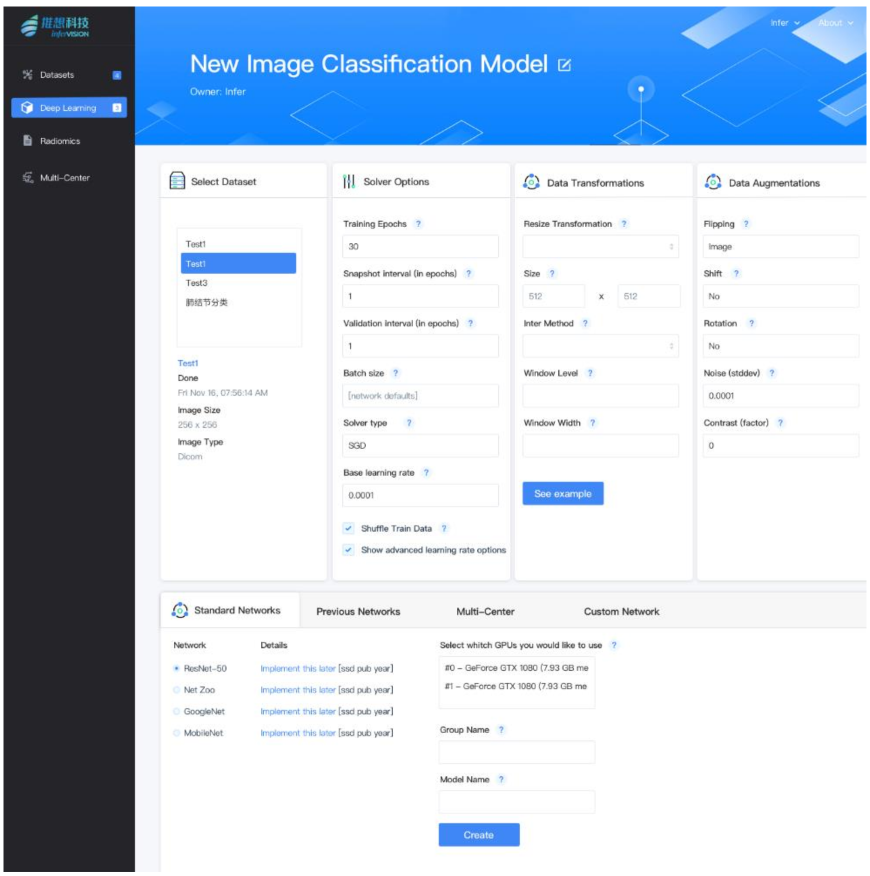


Figure 8. InferScholar's interface for tuning deep learning model parameters.

InferScholar Intelligence Radiomics

This module integrates the complete radiomics feature extraction tools, which can extract radiomics features including, but not limited to, (1) first-order features, (2) shape features, (3) grey level co-occurrence matrix features, (4) grey level size zone matrix features, (5) grey level run length matrix features, (6) neighboring grey tone difference matrix features, and (7) grey level dependence matrix features. The module is suitable for both 2D and 3D images.

For the features mentioned above, except shape feature, they can be extracted from the original and processed images. During extraction, these base features can be freely re-combined thus creating over 4000 features for each image.

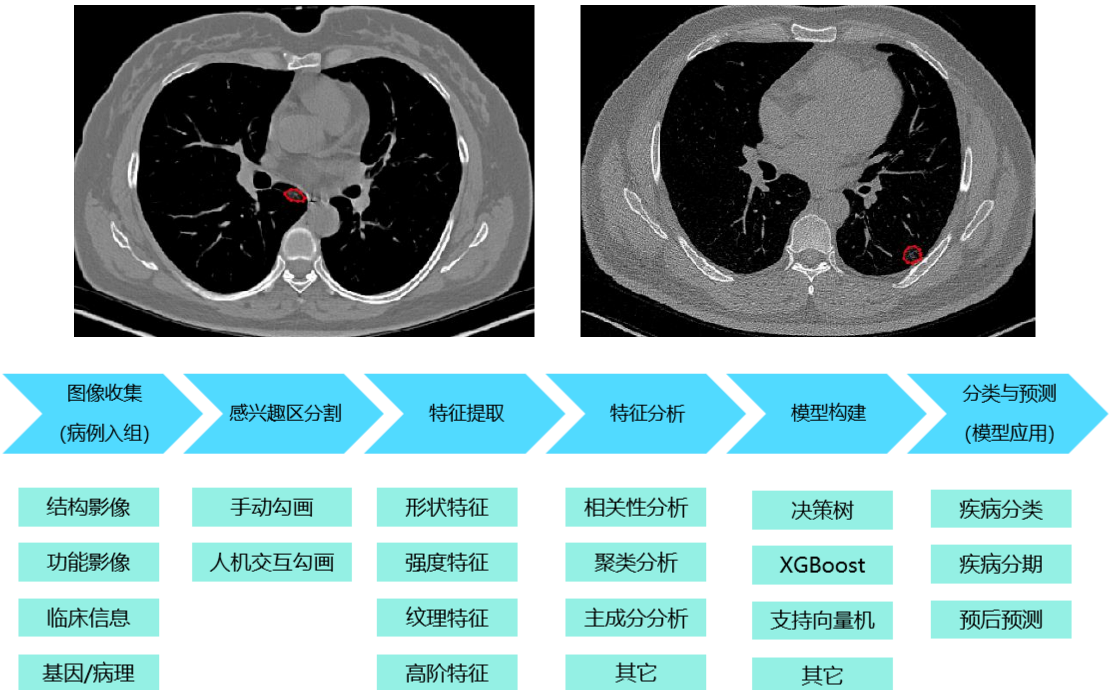


Figure 9. Pipeline of InferScholar Radiomics.

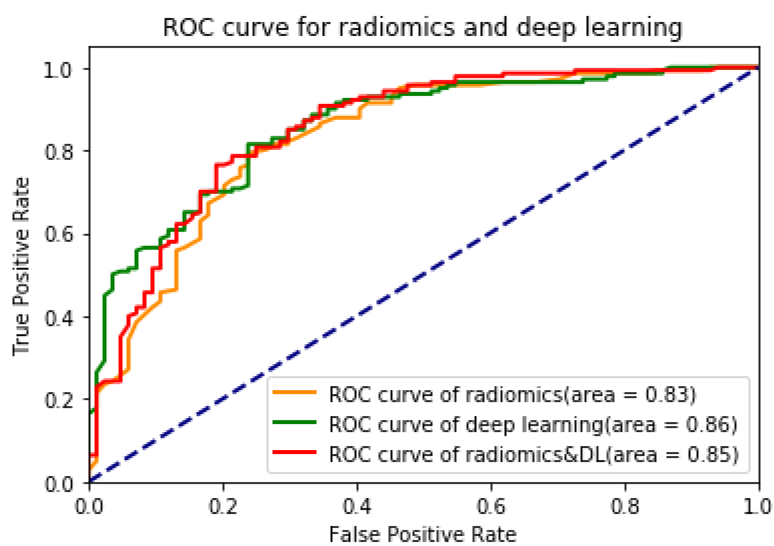
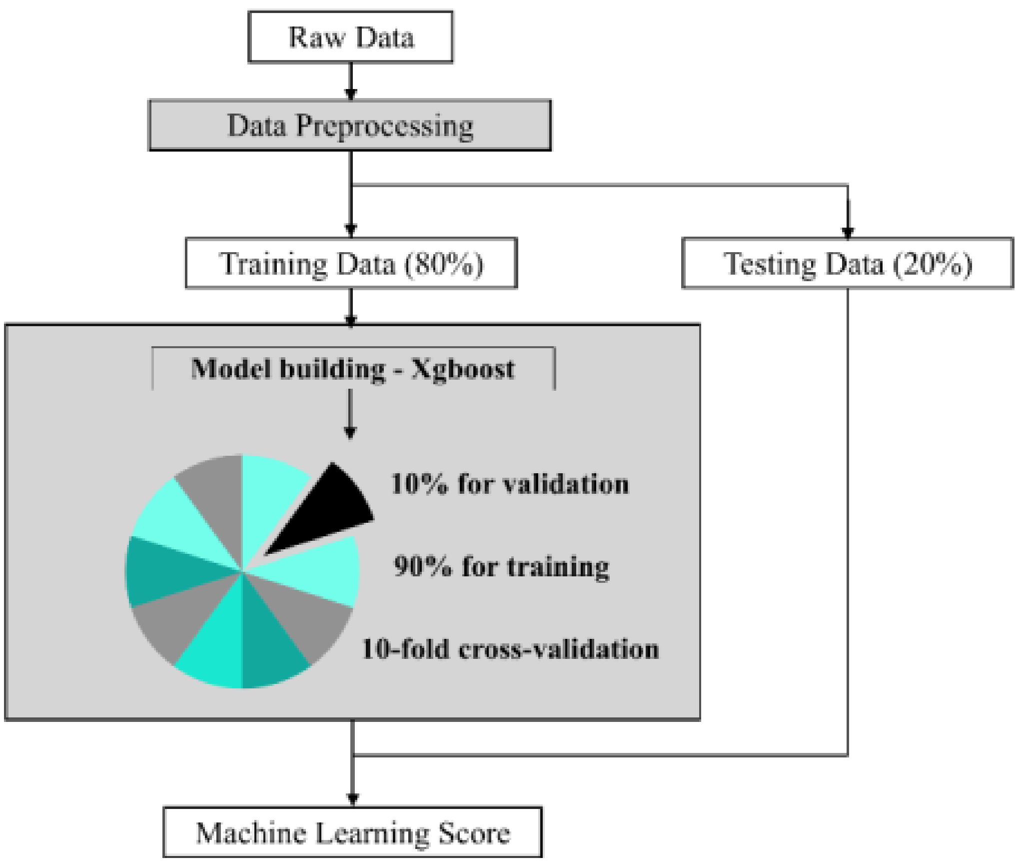


Figure 10. Pulmonary nodule malignancy prediction comparison between deep learning and radiomics using InferScholar.

InferScholar Statistical Analysis and Classic Machine Learning

Infervision's data analysis team can also provide professional services for statistical and classic machine learning modeling for structured datasets (such as epidemiological survey data, experimental control data, etc.). Services include, but are not limited to:

- Classic statistical modeling analysis (for data with various distributions):
    - Hypothesis testing
    - Regression analysis
    - Survival analysis
- Classic machine learning modeling analysis:
    - Decision tree
    - Random forest
    - Generalized linear model
    - Logistic regression
    - Naïve Bayes
    - Supporting vector machine
    - XG Boost
    - k-means
    - others



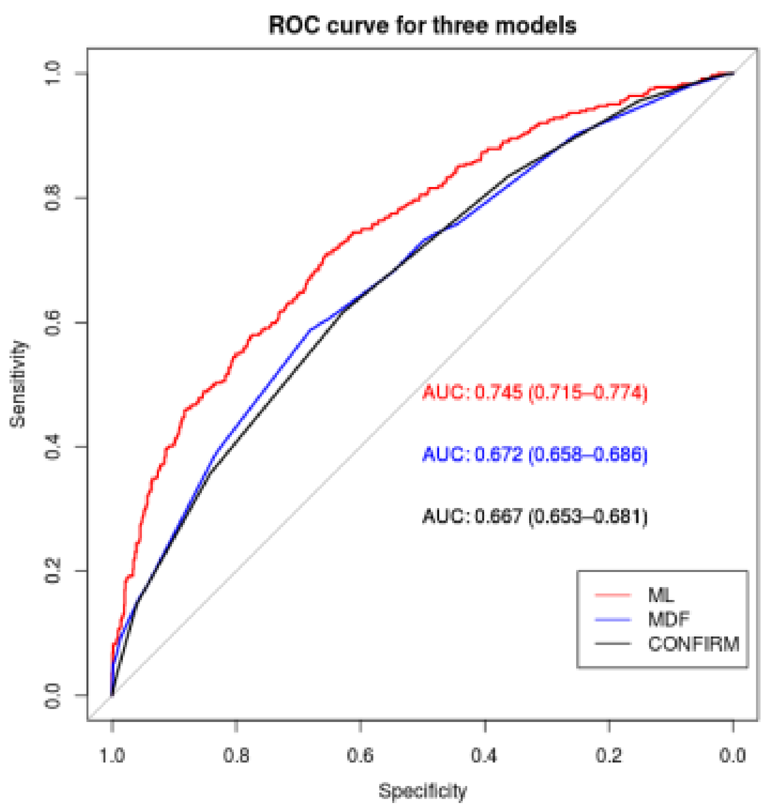


Figure 11. Apply XG Boost algorithms assisting hospitals to predict coronary heart disease based on the screening datasets.