RSNA Press Release

Deep Learning Model Helps Detect Lung Tumors on CT

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OAK BROOK, Ill. (January 21, 2025) — A new deep learning model shows promise in detecting and segmenting lung tumors, according to a study published today in *Radiology*, a journal of the Radiological Society of North America (RSNA). The findings of the study could have important implications for lung cancer treatment.

According to the American Cancer Society, lung cancer is the second most common cancer among men and women in the U.S. and the leading cause of cancer death.

Accurate detection and segmentation of lung tumors on CT scans is critical for monitoring cancer progression, evaluating treatment responses and planning radiation therapy. Currently, experienced clinicians manually identify and segment lung tumors on medical images, a labor-intensive process that is subject to physician variability.

While artificial intelligence deep learning methods have been applied to lung tumor detection and segmentation, prior studies have been limited by small datasets, reliance on manual inputs, and a focus on segmenting single lung tumors, highlighting the need for models capable of robust and automated tumor delineation across diverse clinical settings.

In this study, a unique, large-scale dataset consisting of routinely collected pre-radiation treatment CT simulation scans and their associated clinical 3D segmentations was used to develop a near-expert-level lung tumor detection and segmentation model. The primary aim was to develop a model that accurately identifies and segments lung tumors on CT scans from different medical centers.

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Mehr Kashyap, M.D.

"To the best of our knowledge, our training dataset is the largest collection of CT scans and clinical tumor segmentations reported in the literature for constructing a lung tumor detection and segmentation model," said the study's lead author, Mehr Kashyap, M.D., resident physician in the Department of Medicine at Stanford University School of Medicine in Stanford, California.

For the retrospective study, an ensemble 3D U-Net deep learning model was trained for lung tumor detection and segmentation using 1,504 CT scans with 1,828 segmented lung tumors. The model was then tested on 150 CT scans. Model-predicted tumor volumes were compared with physician-delineated volumes. Performance metrics included sensitivity, specificity, false positive rate and Dice similarity coefficient (DSC). DSC calculates the similarity between two sets of data by comparing the overlap between them. A value of 0 represents no overlap while a value of 1 represents perfect overlap. The model segmentations were compared to those from all three physician segmentations to generate the model-physician DSC values for each pairing.

The model achieved 92% sensitivity (92/100) and 82% specificity (41/50) in detecting lung tumors on the combined 150-CT scan test set.

For a subset of 100 CT scans with a single lung tumor each, the median model-physician and physician-physician segmentation DSCs were 0.77 and 0.80, respectively. Segmentation time was shorter for the model than for physicians.

Dr. Kashyap believes that the use of a 3D U-Net architecture in developing the model provides an advantage over approaches using a 2D architecture.

"By capturing rich interslice information, our 3D model is theoretically capable of identifying smaller lesions that 2D models may be unable to distinguish from structures such as blood vessels and airways," he said.

One limitation of the model was its tendency to underestimate tumor volume, resulting in poorer performance on very large tumors. Because of this, Dr. Kashyap cautions that the model should be implemented in a physician-supervised workflow, allowing clinicians to identify and discard incorrectly identified lesions and lower-quality segmentations.

The researchers suggest that future research should focus on applying the model to estimate total lung tumor burden and evaluate treatment response over time, comparing it to existing methods. They also recommend assessing the model's ability to predict clinical outcomes on the basis of estimated tumor burden, particularly when combined with other prognostic models using diverse clinical data.

"Our study represents an important step toward automating lung tumor identification and segmentation," Dr. Kashyap said. "This approach could have wide-ranging implications, including its incorporation in automated treatment planning, tumor burden quantification, treatment response assessment and other radiomic applications."

"Automated Deep Learning-Based Detection and Segmentation of Lung Tumors at CT." Collaborating with Dr. Kashyap were Xi Wang, Ph.D., Neil Panjwani, M.D., Mohammad Hasan, M.D., Qin Zhang, Charles Huang, Ph.D., Karl Bush, Ph.D., Alexander Chin, M.D., M.B.A., Lucas K. Vitzthum, M.D., Peng Dong, Ph.D., Sandra Zaky, M.D., Billy W. Loo, M.D., Ph.D., Maximilian Diehn, M.D., Ph.D., Lei Xing, Ph.D., Ruijiang Li, Ph.D., and Michael F. Gensheimer, M.D.

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For patient-friendly information on lung cancer, visit *[RadiologyInfo.org](https://www.radiologyinfo.org)*.

Images (JPG, TIF):

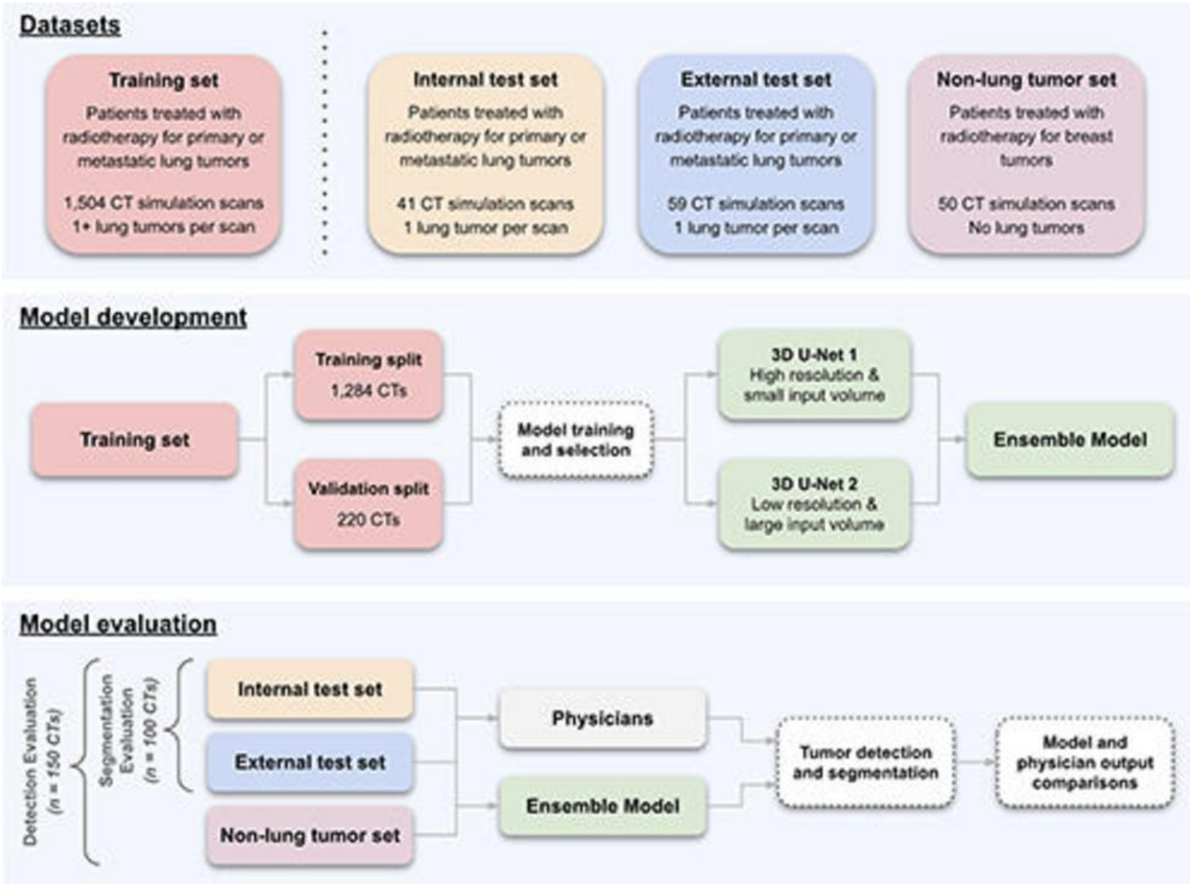

Figure 1. Flow diagram of the datasets and model development and evaluation framework.
[High-res (TIF) version]()

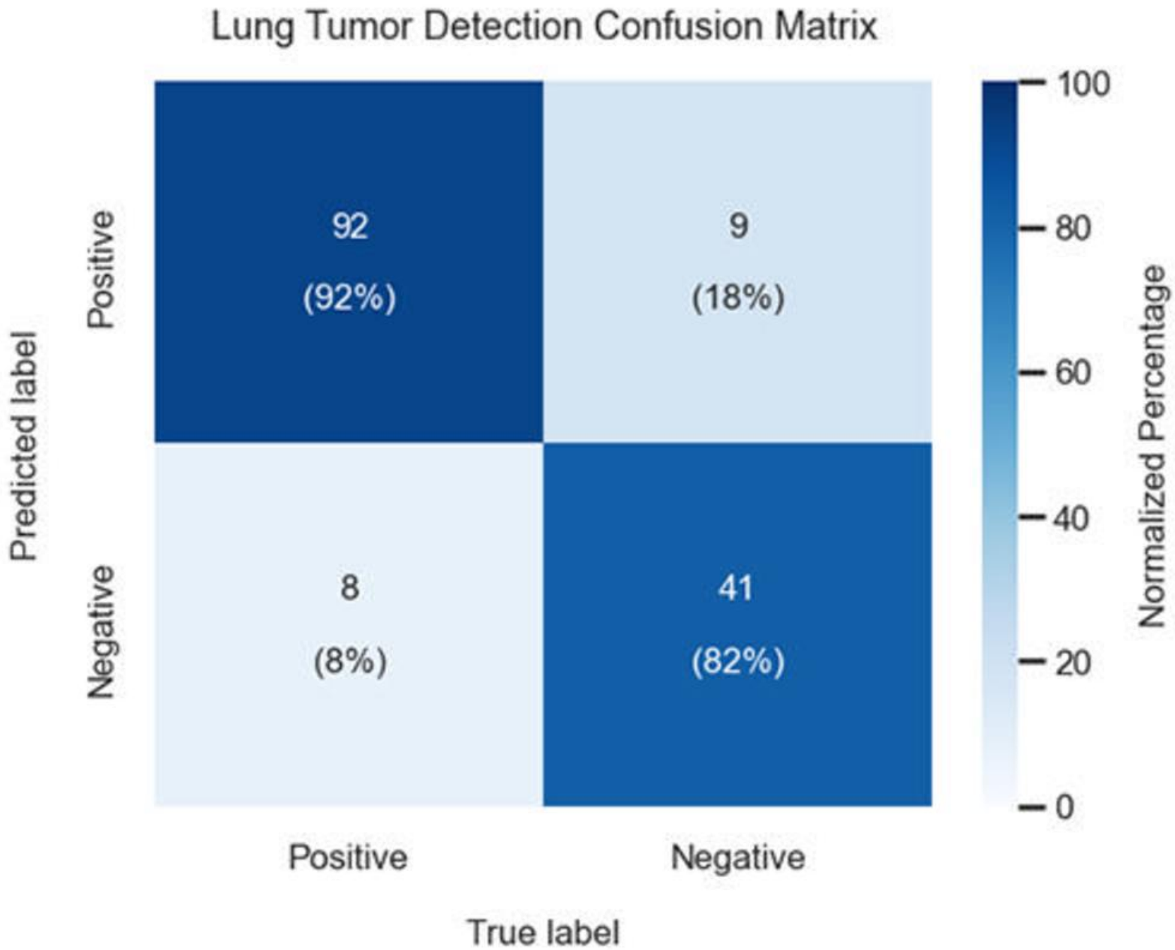

Figure 2. Per-scan lung tumor detection evaluation confusion matrix for the 150 CT scans in the test set. Percentages are determined by dividing absolute numbers by column sums.
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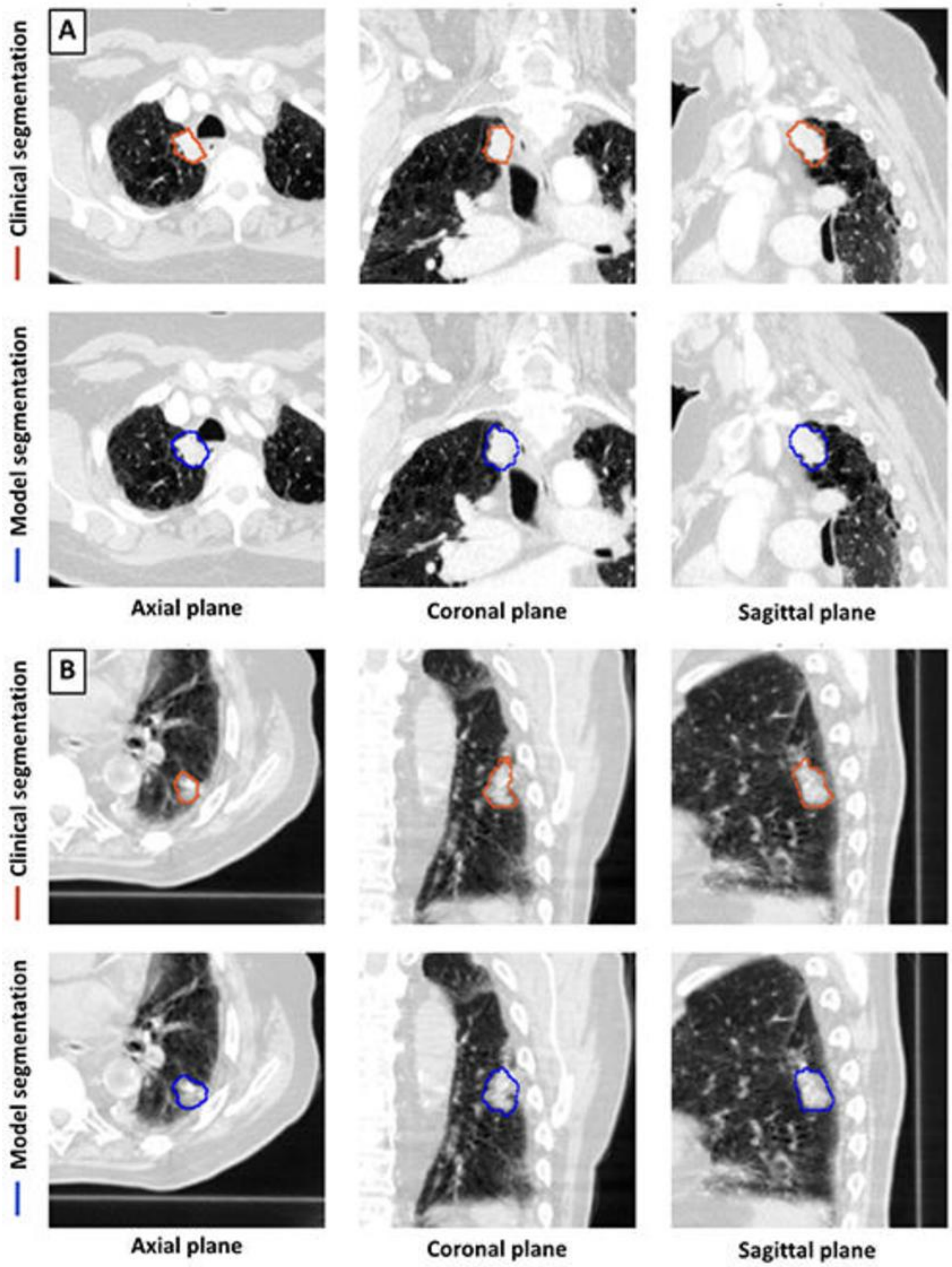

Figure 3. Model and clinical segmentation examples. **(A)** 71-year-old female with non-small cell lung cancer (NSCLC) from the internal test set. **(B)** 87-year-old male with NSCLC from the external test set. Both patients underwent radiotherapy. CT simulation scans acquired prior to radiotherapy are displayed. Clinical segmentations represent the contours developed in the radiotherapy planning process.
High-res (TIF) version

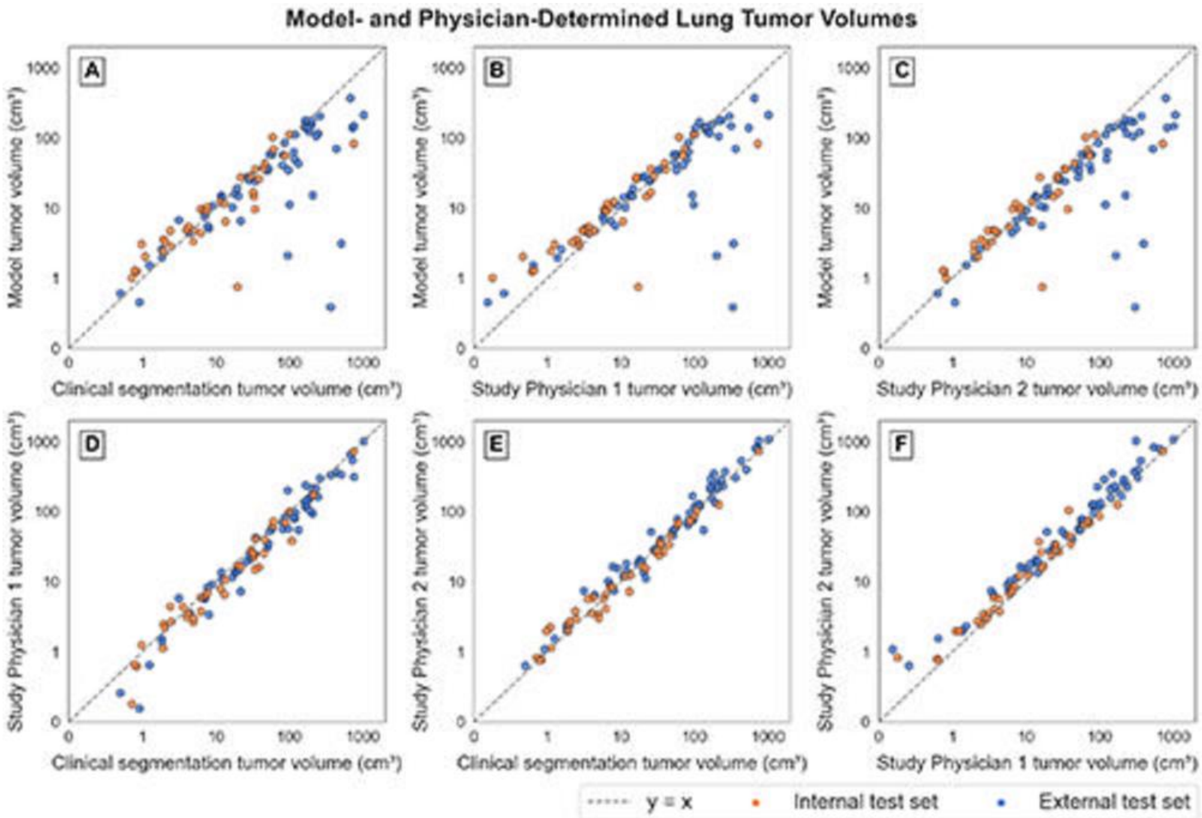

Figure 4. Model- and physician-determined lung tumor volume comparisons. Scatterplots show the relationships between model-determined tumor volumes and those determined by **(A)** clinical segmentation; **(B)** study physician 1; and **(C)** study physician 2. Additional scatterplots compare physician-determined tumor volumes: **(D)** study physician 1 vs. clinical segmentation; **(E)** study physician 2 vs. clinical segmentation; and **(F)** study physician 2 vs. study physician 1. The dotted diagonal line represents perfect agreement (y = x) between the two volume measurements. The orange and blue dots represent data points from the internal and external test sets, respectively.
High-res (TIF) version

Resources:

Study abstract