Research Article

The Clinical Lung Cancer

Lung cancer prediction by Deep Learning to identify benign lung nodules.

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ABSTRACT

It has been suggested that deep learning is a promising method for classifying cancerous nodules. We wanted to use an independent dataset of indeterminate nodules in a European multicenter study to retrospectively validate our Lung Cancer Prediction Convolutional Neural Network (LCP-CNN), which was trained on US screening data. trial, to exclude benign nodules that continue to exhibit a high sensitivity to lung cancer.

Approach : The U.S. National Lung Screening Trial (NLST) CT data was used to train the LCP-CNN to create a malignancy score for each nodule. The LCP-CNN was then validated on CT scans with 2106 nodules (205 lung cancers) found in patients from the Early Lung Cancer Diagnosis Using Artificial Intelligence and Big Data study. three tertiary referral facilities in the UK, Germany, and the Netherlands provided the data for the LUCINDA study. By determining criteria on the malignancy score that achieve at least 99% sensitivity on the NLST data, we were able to pre-define a benign nodule rule-out test that would identify benign nodules while maintaining a high sensitivity. Using Area-Under-the-ROC-Curve analysis (AUC), the overall performance for each validation site was assessed.

Findings : 94.5% (95 %CI 92.6–96.1) was the average AUC for all of the European centers. Utilizing a With a sensitivity of 99.0 %, it was possible to rule out malignancy in 22.1% of the nodules, saving 18.5% of the patients from undergoing follow-up scans. The two false-negative results were indicative of typical tiny carcinoids.

Keywords : Lung cancer ,Screening ,Pulmonary nodule ,Deep learning.

INTRODUCTION

Radiologists have a difficult time accurately differentiating between benign and malignant small-to-intermediate sized, 5–15 mm lung nodules found by computed tomography (CT). As CT scanners have become more advanced, more of these pulmonary Both in the context of ordinary clinical care and lung cancer screening, nodules are found. One lung nodule affects about 50% of smokers [1], and 25% have more than one. Less than 1% of these nodules are malignant [1]. Based on nodule type, size, and growth, Fleischner and Lung-RADSTM guidelines [2,3] classify nodules for both incidentally identified and screening detected lesions.

These nodule management procedures still have a significant false-positive rate even with their extensive use.

A number of recent research have suggested characterizing pulmonary nodules using artificial intelligence (AI), and specifically Deep Learning, in order to reduce the number of scans required to determine if a nodule is benign or cancerous. [4] As of right now, the Given that most of these investigations include bigger nodules up to 30 mm in diameter, the sensitivity of these instruments is only moderate. Since most lung malignancies are larger than benign nodules, the large nodule size leads to biased data sets. Thus, it is still up for debate whether these Deep Learning techniques find features unique to lung cancer or just classify nodules according to size.Many follow-up CT exams may be avoided if a convolutional neural network (CNN) was trained to recognize benign nodules specifically rather than just possibly-malignant lesions. We Using data from the National Lung Sceening Trial (NLST), a CNN trained for the purpose of lung cancer prediction (LCP CNN) was created. It was then programmed to particularly identify benign nodules, allowing them to be “ruled out” of needless follow-up with a high degree of accuracy. [5]

It was recently demonstrated that the LCP-CNN performed better for lung nodule risk categorization than the Brock University model after validation using a retrospective UK dataset [6]... A second study demonstrated that nodules could be categorized into high-risk (65% malignancy threshold) and low-risk (5% malignancy threshold) groups using the LCP-CNN. enhanced precision in comparison to conventional risk prediction models [7]. In order to rule out benign nodules while keeping a high lung cancer sensitivity, the study’s objective was to verify the LCP-CNN on an independent dataset of small-to-intermediate sized (5− 15 mm) nodules in a European multicenter experiment.

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METHODS

Training of the LCP-CNN

We used the NLST dataset to train the LCP-CNN. Previous descriptions exist for the study design and NLST inclusion criteria.(7) There were 10,368 participants in all in this dataset: 9310 individuals who were 1058 people had lung cancer and solely benign lung nodules. We classified all nodules as malignant in the training set (N = 932 in 575 individuals) if they could be conclusively connected in retrospect to a diagnosis of lung cancer. In the context of the NLST (screening and follow-up until seven years after baseline), we considered all nodules in patients (N = 14,761 in 5972 participants) who had not been diagnosed with lung cancer as benign nodules. Publications [7] have details about the training set.With these data, the LCP-CNN was trained to use supervised learning to distinguish between benign and malignant nodules straight from the CT scan. The system gains knowledge by modifying its parameters until the predictions align with the verified truth of the nodules.evaluation. After training, the model (i.e., the LCP-CNN classifier generates a malignancy score per nodule) can forecast the likelihood that a new node would be benign or cancerous. Next, we established a benign nodule rule-out. test by setting a 100% target sensitivity threshold based on the NLST data's malignancy score (i.e., no tumors missed). Using an eight-fold cross-validation method, the ruleout levels were established.

RESULTS

Nodule characteristics

The validation set contained a total of 1650 unique individuals (201 of whom had lung cancer, 12.2%), with 2106 distinct nodules (205 of whom were malignant, 9.7%) (Fig. 1). With a range of 19–94, the median patient age was 63.0. There were 489 women (29.6%). Table 1 lists the nodule's characteristics. Tables A1 and A2 in the Appendix contain more precise data on the location and size of nodules.The LCP-CNN's performance varied depending on the site when it came to identifying benign nodules. Between the three centers, the overall AUC (Fig. 2) was 94.5 % (92.6 %CI 92.6–96.1). AUCs were found for sites A, B, and C, respectively. 98.5% (95 %CI 84.5–91.3), 97.7% (95 %CI 95.9–99.0), and 88.1% (95 %CI 96.6–99.6). When center A and C's AUCs were compared, they performed noticeably better than center B ($p < 0.01$ and $p < 0.001$, in that order), a tertiary referral facility where patients often arrived with a significantly higher pre-test chance of lung cancer. There was no discernible difference between centers A and C (p = NS), both individuals having nodules that were primarily discovered by accident.

Benign-rule out performance

With examples found in Figure A1 Appendix, the pre-defined score threshold for a benign nodule yielded an overall sensitivity of 99.0 % (95 %CI: 97.5 %–100.0 %) and specificity of 22.1% (95 %CI: 20.2 %–24.9%). Adverse In both cases, the carcinoids were round, smooth-surfaced, and weighed between 7 and 8 mm. When patients were taken into account rather than just nodules, the software successfully recognized 18.5% (95 %CI: 16.5%–20.6%) of the patients as benign, in which the patient's highest-scoring nodule was taken into consideration when making decisions. The central lobe had ruled-out nodules that were frequently smaller than 8.0 mm (Table A2 Appendix). The prediction accuracy was 99.5%. By applying the benignity threshold score, 420 benign nodules were accurately excluded (of which 11 were initially diagnosed based on histology, 5 on resolution at follow-up, 191 by expert opinion [i.e., perifissural nodules], 133 by volumetric stability after one year, and 80 by diameter stability after two years). Two tumors were given false-negative results (Fig. A2, Appendix).

DISCUSSION

After being trained on lung nodule participants from the NLST dataset, our LCP-CNN performed exceptionally well in identifying benign nodules, accurately ruling out malignancy in one-fifth of patients with small-to-intermediate sized nodules. This suggests that CNNs may be useful for predicting the risk of lung cancer. Prior AI research has demonstrated promise and has concentrated on increasing the percentage of malignancies that are accurately classified (i.e., have a high positive-predictive value). [8] But these tools' sensitivity is still mild, despite the fact that the majority of these studies only included big nodules up to 30 mm in diameter, which limits their clinical applicability. Instead, they focus on small-to-intermediate sized nodules, which are clinically important. The strategy we have verified in this work is to utilize our AI system, the LCP-CNN, to identify benign nodules with a high degree of certainty and to recommend that these nodules may be ruled out, reducing the need for additional workup. This method differs from utilizing AI to identify lung malignancies. decision assistance for lung nodules that were unintentionally discovered. Many patients may be spared needless workup, including imaging and invasive treatments, by eliminating CT scans, which have a very high sensitivity (99.0% in our study). It needs to be prospectively validated in a lung cancer screening program before it can be thought of as a potential application in this context.

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