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SSC09

Science Session with Keynote: Informatics (Artificial Intelligence in Radiology: Bleeding Edge)

Monday, Nov. 26 10:30AM - 12:00PM Room: E450A

AI BQ IN

AMA PRA Category 1 Credits ™: 1.50
ARRT Category A+ Credit: 1.75

FDA Discussions may include off-label uses.

Participants

George L. Shih, MD, MS, New York, NY (*Moderator*) Consultant, Image Safely, Inc; Stockholder, Image Safely, Inc; Consultant, MD.ai, Inc; Stockholder, MD.ai, Inc;
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Sub-Events

SSC09-01 Informatics Keynote Speaker: Bleeding Edge Medical AI

Monday, Nov. 26 10:30AM - 10:40AM Room: E450A

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SSC09-02 Relationship Learning and Organization of Significant Radiology Image Findings for Lesion Retrieval and Matching

Monday, Nov. 26 10:40AM - 10:50AM Room: E450A

Awards
Trainee Research Prize - Fellow

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PURPOSE

Radiologists mark and measure significant image findings in their daily work to assess patients' conditions and therapy responses. These large-scale and diverse clinical annotations can be great data sources to train data-hungry algorithms (e.g. deep learning) for medical image analysis. However, they are basically unsorted and lack semantic annotations like the lesion type and location. We aim to organize and explore them by learning a deep feature embedding for each lesion. It can help us to 1) know their types and locations; 2) find similar lesions in different patients, i.e. content-based lesion retrieval; and 3) find similar lesions in the same patient, i.e. lesion matching across scans for disease tracking.

METHOD AND MATERIALS

We built a large-scale and comprehensive dataset, DeepLesion, by mining the PACS. It contains 32,735 lesions from 10,594 CT studies of 4,427 patients. The lesions are quite diverse, and include e.g. lung nodules, liver lesions, adenopathy, and bone lesions. The train/val/test sets have 70%, 15%, 15% of the data split in patient level. We learn a feature embedding for each lesion that keeps the similarity relationship of the type, location, and size, i.e. lesions with similar attributes should have similar embeddings. We get the lesion types and locations by label propagation and self-supervised body-part regression. Size is directly obtained from the radiological marking. A triplet network with a sequential sampling strategy is utilized to learn the embedding. The network is a multiscale multi-crop convolutional neural network that can exploit both context and detail of the lesion images. The learned embeddings can be applied in lesion retrieval and matching by nearest neighbor searching.

RESULTS

In the test set of DeepLesion, we achieve 91.5±0.1%, 92.8±0.0%, and 94.9±0.0% accuracy in lesion retrieval w.r.t. the lesions'

type, location, and size, respectively. The area-under-curve value for lesion matching is 95.9% in a manually labeled test set of 1313 lesions from 103 patients.

CONCLUSION

We proposed an algorithm to learn feature embeddings for a variety of lesions to encode their type, location, and size. Experiments showed its effectiveness in lesion retrieval and matching.

CLINICAL RELEVANCE/APPLICATION

The proposed algorithm can be used in content-based lesion retrieval and intra-patient lesion matching, which can help radiologists find similar lesions and track lesions in follow-up studies.

SSC09-03 Multi-Stage Deep Disassembling Networks for Generating Bone-Only and Tissue-Only Images from Chest Radiographs

Monday, Nov. 26 10:50AM - 11:00AM Room: E450A

Participants
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CONCLUSION

Deep neural network based automatic disassembling network for CRs is demonstrated and its performance is validated by SSIM proving its potential to improve interpretability of CRs and aid pysicians for accurate diagnosis.

Background

Dual-energy subtraction technique produces bone-only and tissue-only images to improve interpretability of chest radiographs (CRs). However, the use of this technique was limited because it requires a specialized hardware device for capturing the CRs. In order to overcome this limitation, we developed a deep disassembling networks for CRs (DDCN) which generates bone-only and tissue-only images from a normal CR.

Evaluation

To develop DDCN, we collected a total of 617 CRs with both bone-only and tissue-only images, which were produced by dual energy subtraction technique. To clean the dataset, we excluded 100 cases with suboptimal image quality. Furthermore, we refined the remaining 517 cases using guided filter and non-local means filter to remove image noises. Subsequently, we randomly divided the 517 datasets into the training dataset (n=467) and validation dataset (n=50). We designed a novel two-stage deep convolutional network where the first-stage is designed for observing context of a CR and the second-stage is for producing bone-only and tissue-only images given the first-stage output. The network is constructed with residual architecture, 40 convolutions for the first-stage and 14 convolutions for the second-stage. We quantitatively measured the performance of our network using SSIM which measures the structure difference between a given ground truth image and our network-producing image. In validation dataset, the measured SSIM comparing ground truth tissue-only images and our network-producing results was 0.9678. When we limit the region of interest (ROI) as lung area, the SSIM was measured as 0.9835. In the case of bone-only image, it was 0.9877 and 0.9870 when we limit ROIs as whole image and lung area, respectively.

Discussion

DDCN produces bone-only and tissue-only images from CRs taken by conventional X-ray device. We believe it is the first introduction of deep neural network for disassembling bone and tissue from a CR.

SSC09-04 Non-invasive Tracking of Cancer Evolution using Deep Learning-Based Longitudinal Image Analysis

Monday, Nov. 26 11:00AM - 11:10AM Room: E450A

Participants
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PURPOSE

Tumors are continuously evolving biological systems, and medical imaging is uniquely poised to monitor those changes in patients, before, during, and after treatment. While it is trivial to track tumor lesions over space and time, it is much harder to develop models encompassing all the time points. Here we investigated the use of recurrent deep learning network capable of analysing time series CT images of locally advanced non-small cell lung cancer (NSCLC) patients.

METHOD AND MATERIALS

Dataset A consists of 179 stage III NSCLC patients treated with definitive radiation therapy (581 scans, mean 3.2 scans per patient). This dataset was separated into independent training/tuning (n=107), and test (n=72) cohorts. Transfer learning through convolutional neural networks (CNN) merged with a recurrent neural network was trained on serial scans. Survival was analyzed for a separate test set with AUC and Kaplan Meier curves. Further pathologic response validation of the CNN model was performed on Dataset B (n=79 patients, 158 scans, 2 per patient) treated with chemoradiation followed by surgery. This cohort was used to

validate pathological tumor response and compared to performance with volume change.

RESULTS

Enhanced performance on the test set was observed with the addition of each follow-up scan into the CNN model for 2-year survival (AUC=0.64, 0.69, 0.74, p<0.05), comporable results were demonstrated for one-year survival. The models with 3 follow-up scans showed strong stratification power for high and low risk groups of the predictions using Kaplan-Meier analysis (Log-rank, p<0.05). The hazard ratios for the one-year and 2-year survival models were 6.16 and 2.38, respectively (p<0.05). The CNN model significantly stratified pathological responders and cases of gross residual disease in Dataset B (AUC=0.65, p<0.05), with predictive results comparable to tumour volume change.

CONCLUSION

This study demonstrates promising results using deep learning to combine patient scans at multiple time points to improve clinical survival and response predictions. Pathologic validation of this biomarker was shown on an independent validation cohort.

CLINICAL RELEVANCE/APPLICATION

Tracking of cancer evolution using deep learning applied to medical imaging showed promising predictions of patient outcome and pathologic response, without the need for manual tumor contours.

SSC09-05 Interpretation of Computed Tomography Without Reconstruction: Reading Sinograms to Detect Intracranial Hemorrhage

Monday, Nov. 26 11:10AM - 11:20AM Room: E450A

Participants
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PURPOSE

In the current medical practice, diseases or conditions, such as intracranial hemorrhage (ICH), are usually diagnosed using reconstructed images that are generated from sophisticated reconstruction algorithms. In this study, we explore the feasibility to directly detect ICH from non-contrast head computed tomography (CT) in data domain instead of image domain by applying deep learning techniques on CT sinograms.

METHOD AND MATERIALS

A total of 889 head CT examinations were retrieved from our institutional database, and each axial slice was annotated by 5 board-certified neuroradiologists. The pixel values of CT images were then converted into linear attenuation coefficients, upon which the 2D parallel-beam Radon transforms were applied to generate simulated sinograms. To investigate the effects of number of projection views and detector size on ICH detection, 3 sets of sinograms were produced: '360 x 729', '120 x 240' and '40 x 80', where 'm x n' means the sinogram obtained from m projection views and n detectors. The sinograms were then randomly splitted into training (635 cases), validation (127 cases) and testing (127 cases) sets, which were used to train, validate, and evaluate a convolutional neural network (CNN) that inputs a sinogram and outputs the probability of ICH. To improve generalization, data augmentation was used for training by applying affine transformations (translation, scaling, rotation and reflection) on CT image slices followed by Radon transforms. For comparison, another CNN was built and trained with reconstructed CT images.

RESULTS

The CNN model using CT images as inputs achieved 91.5% test accuracy on ICH detection, and the models using "360 x 729", "120 x 240" and "40 x 80" sinograms as inputs detected ICH with 80.2%, 78.1%, and 76.7% accuracy, respectively.

CONCLUSION

This study shows the potential of direct detection of ICH using CT raw data without image reconstruction. The results also suggest the possibility of using sparse projection views and large-size detectors without sacrificing the ICH detection accuracy, which could lower the radiation dose and equipment costs.

CLINICAL RELEVANCE/APPLICATION

Direct detection of critical conditions like ICH using sinograms without image reconstruction will save the processing time that is critical in situations like emergency rooms. The potential of radiation dose and equipment cost reduction is also of interest to radiologists.

SSC09-06 Image Annotation by Eye Tracking: Accuracy and Precision of Centerlines of Obstructed Small Bowel Segments Placed Using Eye Trackers

Monday, Nov. 26 11:20AM - 11:30AM Room: E450A

Participants
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PURPOSE

To determine the accuracy and precision of centerlines of obstructed small bowel segments placed using eye trackers.

METHOD AND MATERIALS

This HIPAA-compliant IRB-approved retrospective pilot study included seven subjects diagnosed with small bowel obstruction (SBO) by CT. For each subject, an obstructed segment of bowel was chosen. Three observers then annotated the centerline of the segment with three methods: manual fiducial placement or visual fiducial placement using either a Tobii x3-120 or 4c eye tracker, which report the location on the screen at which an observer is looking. This location was mapped to 3D coordinates within the CT volume using a custom 3D Slicer module. Each annotation was repeated three times. The distance between centerlines was calculated after alignment using dynamic time warping (DTW) to account for the variable number of fiducials placed. Intra-observer DTW distance between manual and visual centerlines was calculated as a measure of accuracy. Intra- and inter-observer DTW distances between centerlines placed with each method were calculated as measures of precision. One-sample t-tests were performed to assess whether mean DTW distances were less than 1.5 or 3 cm for each measure of accuracy or precision respectively.

RESULTS

DTW distances between manual and visual centerlines ranged from 1.1±0.2 to 1.8±0.2 cm, and were significantly less than 1.5 cm for two of three observers using both visual methods ($P<0.01$). Intra- and inter-observer DTW distances for manual centerlines were 0.6±0.1 and 0.8±0.2 cm, and for visual centerlines ranged from 1.0±0.4 to 1.9±0.6 cm, but were less than 3.0 cm in all cases ($P<0.01$).

CONCLUSION

Eye trackers may be used for visual annotation of the centerlines of obstructed small bowel segments with accuracy and precision that compare favorably to the threshold diameter of 3 cm for diagnosis of SBO on CT. Accuracy varied among observers, but precision was consistently favorable.

CLINICAL RELEVANCE/APPLICATION

SBO is a common and important disease, for which machine learning tools have yet to be developed. Image annotation is a critical first step in machine learning, but manual annotation of small bowel is prohibitively time-consuming. Image annotation by eye tracking is sufficiently accurate and precise relative to the diameter of obstructed small bowel to serve as a potential first step in the development of machine learning tools that facilitate diagnosis of SBO on CT.

SSC09-07 Big Data Interpretability: Automatically Identify Mislabeled Data in Medical Imaging Deep Learning

Monday, Nov. 26 11:30AM - 11:40AM Room: E450A

Participants
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PURPOSE

In big data applications, data quality and variations can significantly influence performance of deep learning models. Manual labeling or natural language processing-based labeling inevitably generates some mislabeled data. We developed a dedicated method for deep learning to automatically identify potentially mislabeled data.

METHOD AND MATERIALS

We proposed a novel algorithm framework using entropy loss and influence functions to measure data's relevance and correlation strengths with respect to classification performance in convolutional neural network (CNN) models. We identified a clinically-acquired digital mammographic imaging data and their BI-RADS breast density categories (a/b/c/d). Category a (fatty) and d (extremely dense) each has 350 images, while Category b (scattered fibroglandular density) and c (heterogeneously dense) each has 2,000 images. We implemented a CNN-based binary classification model on distinguishing Category a vs d and another similar model for Category b vs c. We did two experiments: 1) Before training models, we purposely flipped the labels for 10% randomly selected data in each category and used our method to identify those flipped data; and 2) We ran our method on the original un-flipped data to identify those potentially mislabeled images by radiologists and evaluate the effect by using a published scheme that assesses the "correctness" of clinically-assigned BI-RADS breast density categories.

RESULTS

The AUC is 0.99 and 0.96 for the Category a vs d model and for the Category b vs c model, respectively. For experiment 1), our method can identify 98% of the purposely flipped data in Category a and d, and 92% in Category b and c, by automatically examining as small as only 30% of the full dataset. For experiment 2), there is 78% (or 96%) overlap in the potentially mislabeled data between those identified by our method and those specified by the "correctness" assessment method, by examining 50% (or 90%) of the full dataset.

CONCLUSION

We developed an automated method for deep learning and demonstrated it can identify vast majority of mislabeled data in the BIRADS-based clinical breast density assessment in digital mammograms.

CLINICAL RELEVANCE/APPLICATION

Fully-automated identification of mislabeled data for deep learning can significantly improve data quality, model's performance and reliability, as well as stratified data interpretability.

SSC09-08 Approaching Chest-CT-Level Performance on Chest X-Rays with Deep-Learning

Monday, Nov. 26 11:40AM - 11:50AM Room: E450A

Participants
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PURPOSE

To determine whether deep learning algorithms can detect abnormalities on chest X-rays (CXR) before they are visible to radiologists.

METHOD AND MATERIALS

We trained deep learning models to identify abnormal X-rays and CXR opacities using a set of 1,150,084 chest X-Rays. We used a retrospectively obtained independent set of de-identified chest X-rays from patients who had undergone a chest CT scan within 1 day (TS-1, n=187), 3 days (TS-3, n=197) and 10 days (TS-10, n=230) of the X-ray to evaluate the algorithms' ability to detect abnormalities that were not visible to the radiologist at the time of reporting on the X-ray. Natural language processing algorithms were used to establish ground truth from radiologist reports of the CT scans, on 2 parameters - 'any abnormality' and 'hyperdense abnormality (HA)' - defined as any abnormal focal or diffuse hyperdense abnormality in the lung fields including but not limited to nodule, mass, fibrosis and calcification. The CT scans were used as ground truth to evaluate the accuracy of the original CXR report and the deep learning algorithms.

RESULTS

Of 187 CT scans in TS-1, 153 contained an HA. 52 of these (34%) had been picked up on the original CXR by the reporting radiologist, and 63 of these (41%) were picked up by the deep learning algorithm. Of 180 abnormal scans in TS-1, 106 (59%) had been picked up as abnormal on the original CXR by the reporting radiologist, and 120 of these (67%) were picked up by the deep learning algorithm. To detect HA, this amounts to an accuracy of 0.49, sensitivity of 0.41 and specificity of 0.85 for the algorithm, versus an accuracy of 0.44, sensitivity of 0.34 and specificity of 0.91 for the original radiologist read of the chest X-ray. To detect any abnormality, the accuracy, sensitivity, and specificity are 0.67,0.67 and 0.71 respectively for the algorithm, and 0.59,0.59 and 0.71 respectively for the reporting radiologist. Similar results were observed on TS-3 and TS-10, as shown in the figure below

CONCLUSION

Deep learning algorithms can pick up abnormalities that have been missed on chest X-rays but identified on a subsequent chest CT.

CLINICAL RELEVANCE/APPLICATION

Using deep learning algorithms to screen chest X-rays could result in higher sensitivity at identifying abnormal scans than currently possible, with only a small corresponding increase in the number of false positives.

SSC09-09 A Portable Automated X-Ray Imaging System and Reading Solution for Screening Lung Diseases

Monday, Nov. 26 11:50AM - 12:00PM Room: E450A

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CONCLUSION

The AXIR system allows clinicians to save time and money while providing patients with good service at any location. The AI-based

automation facilitates its use as a screening and diagnosis tool, allowing doctors to make real-time decisions with high precision and reliability. The system, in the future, may cover other anatomical regions while the AI-engine can be enhanced to diagnose broader disease indications.

Background

A chest x-ray is a commonly used examination for screening and diagnosis of lung diseases. Artificial intelligence (AI) solutions, for automated image analysis, have been implemented as cloud-based solutions centered on hospitals with well-equipped infrastructures. However, two-thirds of the planet does not have access to radiology services due to lack of infrastructure and expertise. We have developed a portable automated X-ray imaging system and reading solution (AXIR) with embedded AI technology to solve this problem.

Evaluation

The AXIR system comprises of a low power portable generator (3kW), a wireless detector (resolution > 4lp/mm), an image pre-processing tool, an AI-based analysis engine, and a mobile viewer. The AI engine screens images for abnormalities and displays the location. Abnormalities can further be classified as pleural effusion, cardiomegaly, opacity, infiltrate, consolidation, fibrosis, hilar enlargement, and calcification. The AI models were trained using public datasets and with images acquired using the AXIR system. The system is being validated at a poor infrastructure site handling about 1000 chest X-rays / month. The performance of the system is evaluated by measuring the accuracy, sensitivity, and specificity of diagnosis.

Discussion

Access to diagnostic imaging services has a great impact on public health and can potentially increase, for example, early detection. AXIR's portable X-ray system with embedded AI-based analytics is a novel highly accessible medical device. In our initial test, we achieved a diagnostic accuracy of 92% with a sensitivity of 94% and specificity of 90%. At our pilot site, the system reduced the diagnosis time from an average of 3 days to less than 10 minutes and brought the patient re-visit rate down to 1% from 20%.