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Deep Learning For Hemorrhage Detection on Head CT: Algorithm Development and Clinical Deployment

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Introduction

Deep learning artificial intelligence is a popular emerging technique with a myriad of potential use cases in diagnostic imaging. However, to date, implementation of these tools in clinical practice remains limited. In this study we attempt to bridge this gap by: (1) developing a highly accurate convolutional neural network (CNN) architecture for detection of hemorrhage on non-contrast CT (NCCT) of the head; (2) developing an end-to-end automated pipeline for CNN deployment including transfer of DICOM images, deep learning enabled identification of CT protocol parameters (presence of contrast, orientation, reconstruction), algorithm prediction and radiologist notification of positive cases.

Hypotheses

1. A custom hybrid 3D/2D CNN architecture can be used for accurate detection of parenchymal and extra-axial hemorrhage on NCCT head.
2. A custom 3D residual CNN architecture can be used for accurate differentiation of CT protocols, a necessary prerequisite for automated identification of the correct input series for CNN hemorrhage detection.
3. A fully automated end-to-end infrastructure for deployment of CNN algorithms will enable live implementation and prospective validation of emerging deep learning tools.

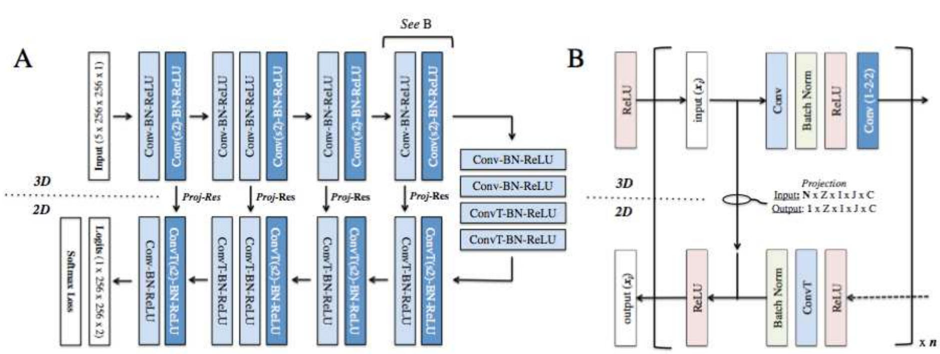
Methods

After IRB approval, all NCCTs acquired between January 1, 2017 and July 31, 2017 at a single institution were downloaded. Using natural-language processing and visual inspection, cases of intraparenchymal (IPH), subarachnoid (SAH), epidural (EPH) or subdural (SDH) were identified. Manual 3D annotations were generated for IPH (voxel-level segmentation masks) and SAH/EPH/SDH (coarse region-of-interest). A custom hybrid 3D/2D CNN (Figure 1) was created for voxel-level prediction of hemorrhage whereby slice-wise prediction was dependent on contextual information from the five immediate slices surrounding the region-of-interest.

Figure 1

Figure 1. Hybrid 3D/2D Architecture For Hemorrhage Detection

(a) Hybrid 3D-contracting and 2D-expanding fully convolutional CNN architecture for prediction of hemorrhage. The contracting arm is composed predominantly of 1 x 3 x 3 convolutions at stride 1 (*light blue*), with an occasional 3D 2 x 3 x 3 convolution at stride 2 to decrease the feature map to 25% of the original (*dark blue*). The expanding arm is composed on entirely of 2D 1 x 3 x 3 convolutional transpose operations. (b) Connections between the contracting and expanding arm are facilitated by residual addition operations between corresponding layers. 3D layers in the contracting arm are mapped to 2D layers in the expanding arm by projection operations.

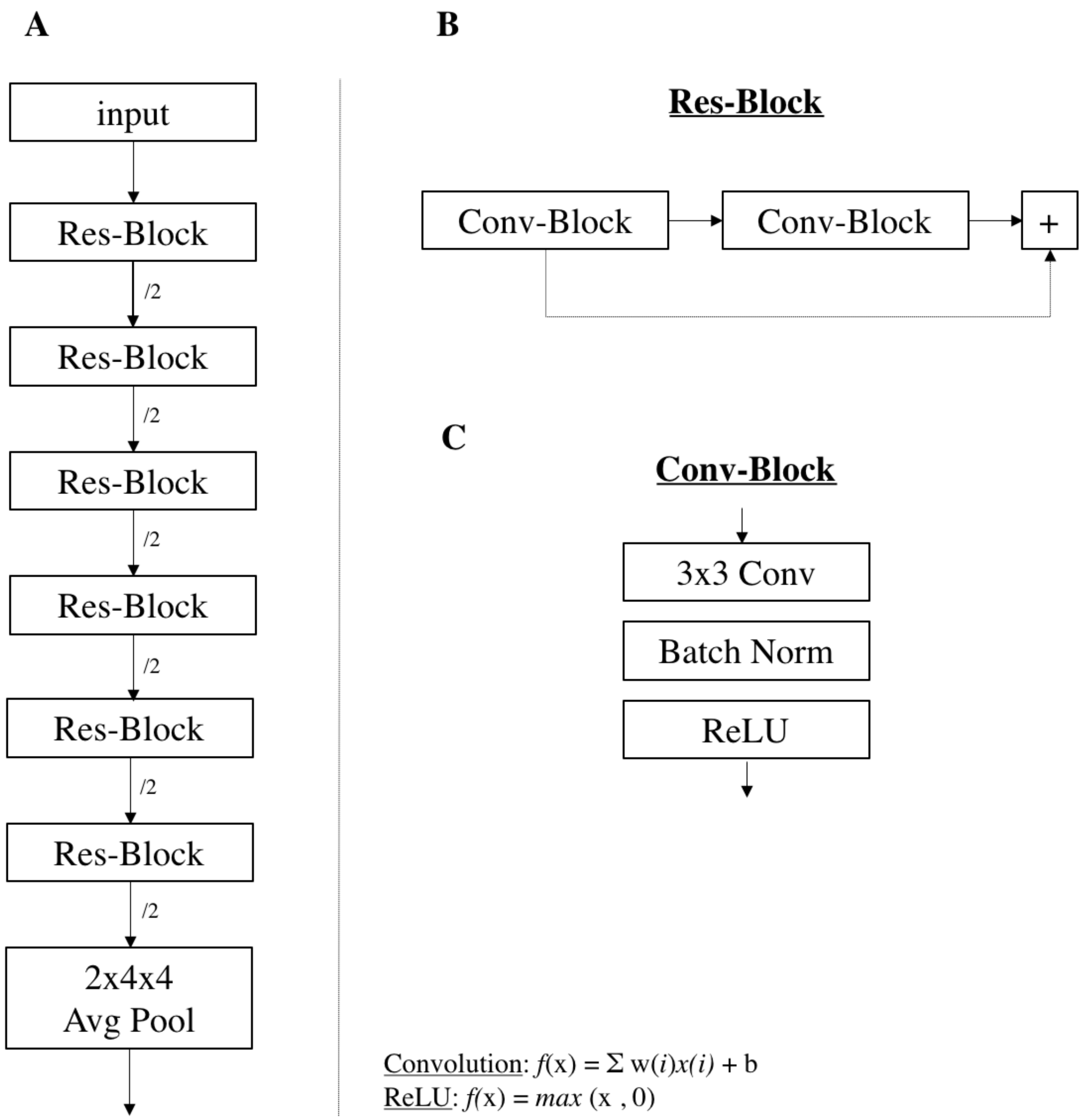


For differentiation of CT protocols, both non-contrast and contrast-enhanced head CT exams obtained in January 2017 at a single institution were identified. All series for all exams were downloaded and separated into the following three categories: presence of contrast; orientation (axial, coronal or sagittal); reconstruction algorithm (soft-tissue or bone). Annotation was performed using a combination of natural-language processing of DICOM headers and visual inspection. A custom 3D convolutional neural network based on residual architecture (Figure 2) was created to map an input 8 x 256 x 256 volume into a prediction for each of the three protocol categories.

Figure 2

Figure 2. 3D Residual Network Architecture For Protocol Identification

(a) Summary of residual neural network architecture for CT protocol identification. A total of six residual blocks are used, subsampling the original 8 x 256 x 256 feature map six times through 2x3x3 convolutions with a stride of 2 in the XY- direction and valid padding in the Z-direction (demarcated by /2 in the figure). (b) Each residual block consists of two serial 1x3x3 convolutional blocks, the latter of which is mapped to the former via an addition operation. (c) Each convolutional block is consists of a 1x3x3 convolution, batch normalization and a ReLU nonlinearity.



Results

For hemorrhage detection, a total of 10,159 NCCTs were identified, 901 (8.9%) of which contained hemorrhage including IPH (n=358; 3.5%), SAH (n=319; 3.1%) and EPH/SDH (n=224; 2.2%), yielding a total of 512,598 images. Upon five-fold cross-validation, the overall algorithm accuracy was 0.971 with AUC, sensitivity, specificity, PPV and NPV of 0.974, 0.971, 0.975, 0.793 and 0.997 respectively. In total only 26/901 (2.9%) of hemorrhages were missed. Further stratification of results by hemorrhage type are shown in Table 1.

Table 1

Table 1. Summary of Results

	IPH	SAH	EDH/SDH	Negative	Total
Positive	353	311	211	229	1,104
Negative	5	8	13	9,029	9,055
Total	358	319	224	9,258	10,159

Key: IPH = intraparenchymal hemorrhage; SAH = subarachnoid hemorrhage; EDH = epidural hemorrhage; SDH = subdural hemorrhage

For CT protocol identification, a total of 1,000 head CT exams were identified yielding a total of 5,623 different series, including: 2,412 non-contrast, 3,192 contrast-enhanced; 3,472 axial, 1,075 coronal, 1,076 sagittal; 2,378 soft-tissue, 3,245 bone reconstructions. Upon five-fold cross validation, accuracy was high for identifying presence of contrast (0.991), orientation (0.998) and reconstruction technique (0.994). Using DICOM headers alone, accuracy was slightly lower for all categories including presence of contrast (0.981), orientation (0.931) and reconstruction technique (0.946).

For algorithm deployment, the following technologies were implemented: automated transfer of head CT acquisition using the Grassroots DICOM (GDCM) library with Python wrappers; anonymization by saving only raw image data as a NumPy binary file; execution of CNNs via the TensorFlow Serving API on a server containing four NVIDIA Titan X Maxwell (12 GB) GPUs; visualization of results on a custom web-based application; notification of positive results via beeper text message implemented using the Python smtplib library.

Conclusions

A customized hybrid 3D/2D deep learning architecture is highly accurate in detection of hemorrhage with only 26 missed cases out 10,159 exams. Furthermore, a separate deep learning tool can be used to determine CT acquisition parameters directly from image data with high accuracy, facilitating full end-to-end deployment of image analysis tools and removing reliance on underlying DICOM headers.

An IRB-approved prospective trial is currently ongoing using the implemented infrastructure for CNN deployment. The algorithm is being utilized as a triage tool to identify positive hemorrhage cases for immediate interpretation, potentially reducing turnaround time and facilitating improved patient outcomes.

Statement of Impact

Combining multiple emerging technologies, a highly accurate deep learning tool for detection of hemorrhage on NCCT can be validated prospectively in the clinical setting.

Keywords

deep learning, convolutional neural networks, stroke, hemorrhage, CT protocols