Identification of Intracranial Hemorrhages From Raw CT Data Using a Convolutional Neural Network

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April 2022

Abstract

Intracranial hemorrhages (ICHs) are time-sensitive injuries that require surgical intervention. They are conclusively diagnosed from a cranial computed tomography (CT) scan after the physical symptoms are recognized. However, in recent years there has been an effort in the field of medical physics to reduce the radiation dose imparted to patients. Here, I investigate the use of a convolutional neural network (CNN) that interprets the raw CT data from partial scans of a patient's head, and attempts to classify whether the patient has an ICH or not. A CNN interpreting raw CT data of partial scans would reduce the radiation dose given to the patient and would lessen the time from the CT scan to the diagnosis. These partial scans were centered at 45°, 90°, and $135^\circ$with respect to the sagittal plane, with the scan widths at each location being 30°, 60°, and 90°. A CNN with the same structure was trained for each set of data described, ten models in total. The validation accuracies for each model were all within the range of 84-85%, and were not affected by the scan width or scan location. This result is inconclusive, and not reasonable with what one would expect. Future work is needed to discern where the issue is in the implementation of this investigation. There is potential to improve the quality of patient care by using CNNs to make decisions from data that a human expert could not interpret.

1 Introduction

1.1 Intracranial Hemorrhages and CT Scans

Intracranial hemorrhages (ICHs) refer to bleeding within the skull, most often the result of trauma or a stroke. There are four categories that encompass ICHs: subdural hematomas, blood that has pooled between the dura and the arachnoid mater; subarachnoid hemorrhages, bleeding into the subarachnoid;

intraparenchymal hemorrhages, bleeding into the brain parenchyma; and epidural hematoma, usually the result of a skull fracture causing bleeding into the epidural space [1], all shown in figure 1. These hemorrhages can lead to neural cell death through lack of oxygen delivery, or increased pressure within the skull. Both of these require action as fast as possible if loss of brain function is to be avoided. Computed tomography (CT) scans are typically used to diagnose an ICH when the patient's symptoms point to one[2]. This is because the pocket of blood in the brain attenuates the x-ray beam more so than the surrounding tissue, providing good contrast on a CT image.

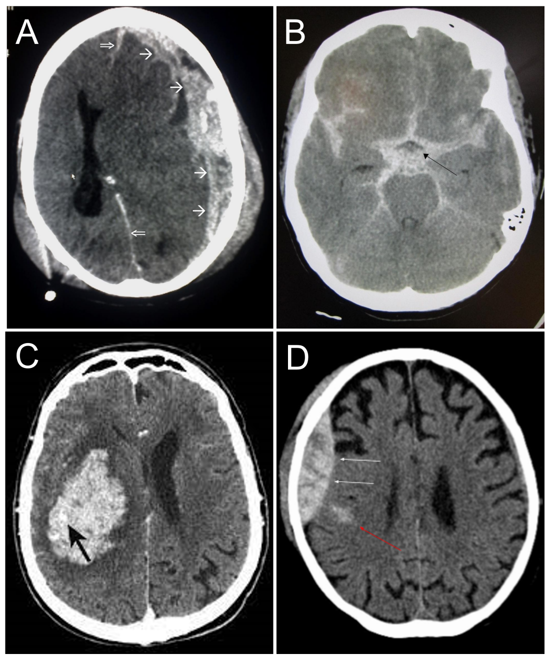

Figure 1: Figure1a shows a subdural hematoma, 1b shows a subarachnoid hemorrhage, 1c shows an intraparenchymal hemorrhage, and 1d shows an epidural hematoma.

When it comes to prescribing a CT scan for further diagnosis of a patient, there are more considerations than just whether a CT scan could provide helpful information for a diagnosis. One must consider the radiation dose given to the patient during the scan. Even though CT scans only comprise 11% of x-ray imaging procedures in the United States, it accounts for more than 67% of the radiation dose from all imaging procedures (including nuclear medicine)[6]. Reducing the dose delivered to the patient will worsen the quality of the diagnostic image, which means that there is a trade-off between reducing the patient dose versus the image quality. In general, the patient dose will only be reduced if it does not impact the ability of the radiologist to interpret the image. In all, CT scans are very helpful in diagnosing ICHs in a patient, but must be prescribed in a responsible manner.

1.2 Machine Learning With CT Scans

The field of computed tomography has many areas where machine learning algorithms could be introduced to improve the level of care for patients. However, there is a large barrier to creating and implementing such models because CT scans are inherently not open for anyone to view or distribute[3]. The DICOM file must be scrubbed of any identifying information and the data set must be annotated, both of which are time consuming tasks for medical professionals who have responsibilities for the care of their patients. Even still, the areas of patient care that machine learning can improve include, but are not limited to, automatic diagnosis[3], diagnosis of disease severity[4], or image reconstruction [5]. With regards to image reconstruction, machine learning algorithms enable the reconstruction of comparable diagnostic images with less radiation dose given to the patient. This is because the algorithm can reconstruct images from CT data that was sampled at 1/16 or even 1/32 the rate of normal CT data[7].

What these areas have in common is that the algorithm either interprets or creates diagnostic images intended for viewing by a radiologist. However, neural networks do not need to interpret the same representation of data that a radiologist would. If a neural network were to interpret raw CT data, called a sinogram, it would reduce the time from the patient's scan to the patient's diagnosis (as compared to the CT data being reconstructed and interpreted by a radiologist). The objective of this paper is create a convolutional neural network (CNN) that can identify whether there is an intracranial hemorrhage present from only a subset of the raw sinogram data of a CT scan.

2 Related Work

Lee et. al have demonstrated that neural network interpretation of sinograms can have results that are comparable to or better than networks that interpret reconstructed images[8]. Their efforts focused on body part recognition and intracranial hemorrhage detection from fully sampled, moderately sampled, and sparsely sampled CT data. They trained an algorithm, called SinoNet, on the fully, moderately, and sparsely sampled sinograms in order to investigate the algorithm's robustness to the amount of data present. An existing CNN, called Inception-v3, was trained to make the same decisions as SinoNet, except it interprets the diagnostic images reconstructed from the fully, moderately, and sparsely sampled sinograms. Lee et. al found that SinoNet outperformed Inception for every sampling rate of data (specifically, the unwindowed, full dynamic range data) when attempting to identify ICHs. This shows that ICH diagnosis from a neural network without image reconstruction or windowing can be a preferable option to a neural network that is trained on reconstructed images.

3 Methods

3.1 Data Collection and Processing

A total of 2000 DICOM files were downloaded from the "RSNA Intracranial Hemorrhage Detection" data set, courtesy of the Radiological Society of North America (RSNA)[9]. The number of images was chosen to be 2000 due to file storage constraints. These images fall into six classes: no hemorrhage, intraparenchymal hemorrhage, intraventricular hemorrhage, subarachnoid hemorrhage, subdural hematoma, or epidural hematoma. The hemorrhage classes are not exclusive, so an image may belong to two or more hemorrhage classes. For the purposes of this investigation, the classes for identification were consolidated into images with no hemorrhage, or images with any type of hemorrhage. Since raw CT data was not accessible for my purposes, I transformed the DICOM images into simulated sinograms via the Radon transform[10]. Of these images, 1900 were randomly selected for the training data and the other 100 were used for the validation data.

3.2 Convolutional Neural Network

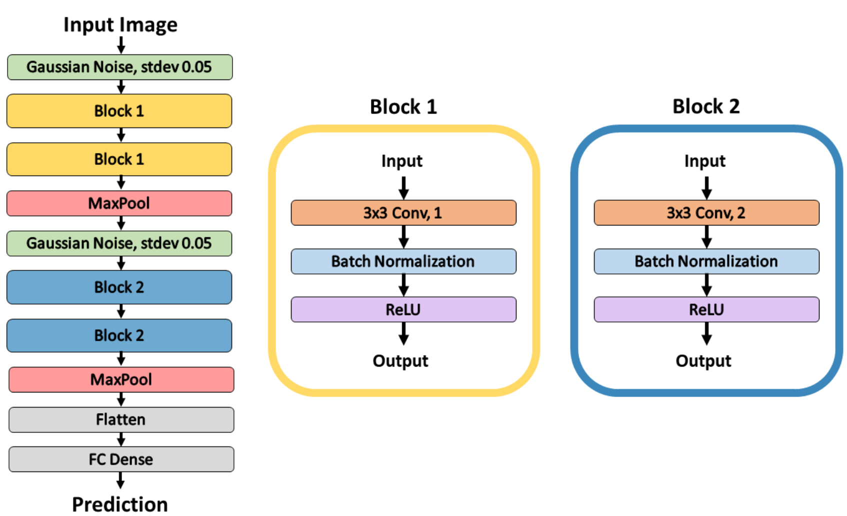

Figure 2: Overall network architecture of the network.

TensorFlow was used to build the structure of the network to create the convolutional neural network (CNN) for this investigation, which is shown in figure 2. The weights were initialized through TensorFlow's default weight initialization when using the "Sequential" method of the "models" class. The performance of this model was evaluated in 10 different situations, the first of which being trained on full sinograms. The other 9 fall into three different categories of where around the head that the partial scan (subsection of the sinogram) is located: at 45°, 90°, and 135°, where 0°is parallel with the sagittal plane. For each of these three categories, three widths of scan arc were used: 30°, 60°, and 90°. The validation accuracy of the model was compared across these ten different situations using the "fit" method of the "model" class. All models were trained for 10 epochs, used the Adam optimizer with a learning rate of 0.01, used the binary cross entropy loss function from TensorFlow, and had a batch size of 100.

4 Results

Figure 3 shows the validation accuracies for the ten models trained to identify intracranial hemorrhages in this investigation. The full scan model had a validation accuracy of 0.84. The models for the scans centered at 45°had validation accuracies of 0.84, 0.84, and 0.85 for scan widths of 30°, 60°, and 90°, respectively. The models for the scans centered at 90°had validation accuracies of 0.84, 0.84, and 0.85 for scan widths of 30°, 60°, and 90°, respectively. The models for the scans centered at 135°had validation accuracies of 0.84, 0.84, and 0.84 for scan widths of 30°, 60°, and 90°, respectively.

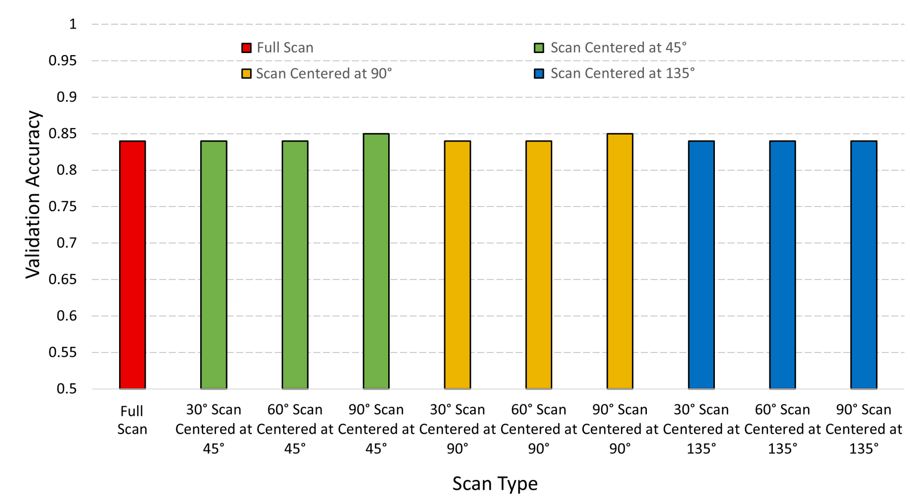

Figure 3: Validation accuracy results of the ten models trained on varying scan widths and scan locations. The red bar represents the full scan model. The green bars represent the models for the scans centered at 45°. The yellow bars represent the models for the scans centered at 90°. The blue bars represent the models for the scans centered at 135°.

5 Discussion

The validation accuracy staying relatively unchanged between the full scan model and the partial scan models, which were all trained on different subsections of the data, is not a reasonable result. One would expect the validation accuracy of a 30°scan to be notably less than that of a 90 °scan across all categories, and even more notably compared to the full scan model. This was not the case, possibly due to a number of reasons. A possible factor was a poor choice of hyperparameters for the training. This is a possibility because the model would seem to find the same local minimum each time based on the loss training loss value. The range of learning rates that were used when attempting to develop the final model all lead to this same result, but the "ideal" learning rate may have been outside the range of values attempted. The problem was not due to over-fitting, as the training accuracies all landed in that 0.84-0.85 range that the validation accuracies lie in. Attempts to discern the problem included shuffling the training data each epoch, changing the type of optimizer and/or loss function used, increasing or decreasing the number of layers or convolutional filters, and using a different set of DICOM images from the RSNA data set. All attempts either produced a model with lower validation accuracy, or hit the same ceiling of 0.84-0.85. For future testing, utilizing more than only 2000 images of the RSNA data set, which contains 752,807 images, could be helpful in discerning the problem (storage space permitting).

In conclusion, this investigation into the use of convolutional neural networks for identifying intracranial hemorrhages from a subsection of raw cranial CT data was inconclusive. This is an area that is worth pursuing due to the possible reductions in patient dose (on the scale of 1/16 to 1/32) and decreasing the time from a CT scan to the patient entering the operating room.

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