Intracranial hemorrhage classification with deep learning

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Abstract— Here goes abstract

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I. Introduction

Intracranial hemorrhage (ICH) is a serious medical condition which if untreated leads to severe disability or death. ICH is usually defined as bleeding occurring inside the skull and can be further categorized based on location of the hemorrhage. These subtypes are:

- Epidural – Located above dura mater which is the first protective layer below skull, wrapping the brain
- Subdural – Located between dura mater and arachnoid which is the second protective layer
- Subarachnoid – Located below arachnoid.
- Intraparenchymal – Located the brain itself
- Intraventricular – Located inside of brain ventricles hollow spaces within brain.

Statistics show that there are 40 000 to 67 000 cases each year in the US. Furthermore, 40% of patients diagnosed with ICH die within 30 days [1] and half of the mortality occurs within first 24 hours [2]. Quick and accurate diagnosis and effective treatment is therefore extremely important in these cases. There are multiple causes of ICH but one of the main ones is stroke which accounts for approximately 15% of the cases [1].

Computed tomography (CT) is the most common tool for ICH diagnosis [2]. CT is preferred because it is usually available in most medical centers and it is a non-invasive method. CT scan can also help with localization and size estimation of the hemorrhage. The diagnostic process in most medical centers is, however, often suboptimal both in its duration and accuracy [3]. The interpretation of CT scans is often done by junior radiologists and is later reviewed by senior staff. Studies show that the initial assessment is often wrong [4] and as result the necessary treatment might not be delivered in time. An automated diagnostic tool such as the deep learning models reported in this paper might help improve the current diagnostic process both in terms of speed and precision.

Recently, machine learning and artificial neural networks especially proved to be efficient in medical image analysis [5].

II. Dataset

The data was published by Radiological Society of North America as part of their competition in collaboration with Kaggle. The dataset comprises of 674258 computed tomography (CT) scans of head stored as DICOM images. The images were assembled from multiple CT studies done by Stanford University, Thomas Jefferson University, Unity Health Toronto and Universidade Federal de São Paulo. Each image was hand labeled by volunteers from the American Society of Neuroradiology. There are 6 classes: epidural, subdural, subarachnoid, intraparenchymal, intraventricular and any. The last class equals 1 when at least one type of the hemorrhage is present and 0 if no hemorrhage is present. The images can belong to multiple classes, i.e. contain more than one type of hemorrhage. An example of raw image is presented in figure 1.A.

A. Class balance

The number of samples per class differs greatly. There are 577155 images of normal patients, i.e. without any hemorrhage, and 97103 images with hemorrhage(s) present.

In table 1, both the probabilities of each hemorrhage type given a CT scan p(H) and the probabilities given CT scan that contains a hemorrhage p(H|any=1).

In this paper, we deal with the class imbalance in two ways. First, we use undersampling to balance the amount of normal and hemorrhage images. In other words, we reduced the number of normal images to the number as the hemorrhage images by random sampling. After undersampling, the dataset consists of 194082 images.

Second, weights were introduced to the loss function. The class weights are indirectly proportional to the class sample size so that misclassification of class with small number of images results in higher loss.

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