ANALYSIS OF CIRCULATORY SYSTEM PATHOLOGIES IN HEAD CT DATA – HEMORRHAGE LOCALIZATION

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Abstract

Acute ischemic stroke and intracranial hemorrhages (ICH) represent critical situations for the patient. Rapid accurate diagnosis and therapy are required to prevent serious lifelong consequences or death. In the case of suspected head circulatory pathology, computed tomography (CT) is often the first choice among imaging techniques because of its availability, speed and reliability. In order to refine and speed up the diagnostic process, advanced algorithms implemented in computer aided diagnosis systems are currently being developed. This paper presents approaches to an automatic ICH localization as a part of a research project aimed at the development of machine learning methods for the analysis of circulatory disorders in head CT scans. Three designed deep learning-based algorithms are described and compared for prediction of the exact position of ICH within a 3D CT scan, and in two cases also for classification into the sub-types. An objective evaluation of the methods is presented along with a discussion of the results. Further possibilities for circulatory diseases analysis in head CT scans using modern algorithms are also discussed.

Keywords

CT, convolutional neural network, deep learning, intracranial hemorrhage, localization, classification

Introduction

The project focusing on the analysis of head computed tomography (CT) scans had its origins in the contractual cooperation of the Department of Biomedical Engineering (Brno University of Technology) with Philips.

Since 2019, the analysis of head circulatory system disorders has been in progress, which has mainly been done by using modern machine learning methods. A part of the research aimed at automatic intracranial hemorrhages detection and localization within the CT scan—i.e., finding their position. This paper brings together outputs of the partial research aimed at localization. The design and comparison of three proposed deep learning-based methods are described.

Motivation

Head circulatory system pathologies represent critical situations with a high incidence that can cause serious lifelong consequences or even death of the patient. A distinction is made between hemorrhagic pathologies (hemorrhagic stroke or other intracranial hemorrhage) and non-hemorrhagic pathologies, where ischemic strokes belong [1]. In the case of cerebral hemorrhage, intraparenchymal (IPH) and intraventricular hemorrhages (IVH) are differentiated according to anatomical position. Extracerebral hemorrhage is divided into subdural (SDH), epidural (EDH) and subarachnoid (SAH) [2].

CT without administration of contrast agent is the first choice among imaging techniques in case of suspected vascular events due to its availability, speed and reliability [3, 4]. Acute hemorrhage appears as a brighter area in CT data compared to the surrounding brain tissue, whereas chronic hemorrhage is manifested by lower Hounsfield Unit (HU) values [2]. Ischemic stroke is characterized in the acute phase by loss of the ability to distinguish between gray and white matter and later by local hypo-attenuation of brain tissue. In the acute phase, a brighter thrombus is sometimes visible in the vessel [3].

Time plays a crucial role in cerebral circulatory pathologies and, in general, the prognosis is better the earlier a correct diagnosis is obtained, and appropriate therapy is planned [1]. However, traditional evaluation of 3D CT data is time consuming, demanding for concentration, and in some cases recognition of pathological structure can be problematic. For example, intracranial hemorrhages (ICH) may be confused with other brighter structures (e.g., calcifications or hyper-cellular tumors) or may be missed due to artifact in the

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image [5]. Early-stage ischemic disorders may generally be difficult to detect in non-contrast CT images and only become more apparent in the sub-acute phase [1, 3]. Magnetic resonance imaging (MRI)-based diffusion weighted imaging (DWI) can most reliably show its presence, but it is often not promptly available at the time of need [1, 3].

Nowadays, intensive development of computer-aided diagnosis algorithms has been in progress. The motivation is the reduction of the time needed for image evaluation, and also avoidance of misdiagnosis. Modern machine and especially deep learning-based methods are becoming dominant in many fields, including medical image analysis, due to their accuracy and efficiency [1].

Related work

According to the basic problem definition, the published algorithms may be divided into methods based on classification, localization and segmentation.

A classification-based solution means assigning a CT image or its slice to a certain class. An example is [6] or [7], where the authors use well-known convolutional neural network (CNN) architectures to classify 2D slices as hemorrhagic or without lesion, respectively, and the type of ICH is determined. In [4], the classification network is combined with a bidirectional "Long Short-Term Memory" (LSTM) module for embedding spatial information and the output is given by determining the type of the whole scan.

Localization methods determine the position of the lesion—its centroid or delimiting area by an orthogonal bounding box (BB). Advantage of localization methods in comparison to classification-based ones is the direct information about the location of individual lesions. The authors [8] predict the BB of acute ischemia in non-contrast CT slices. To do so, they use the well-known YOLO v3 detection network [9] in combination with a CNN classification model to reduce false positives.

The segmentation leads to the labeling of all disease-affected voxels. Main advantage is the precise knowledge of areas affected; however, these methods usually require previous time-consuming labeling on the level of individual pixels. For the segmentation of ICH in 2D slices, the well-known U-net architecture was used in [10]. A similar approach but in 3D is used in [11]. For the case of segmentation of ischemic regions and dense vessels (due to a presence of thrombus) in non-contrast CT images, the CNN model together with an anatomical atlas is used in [12] and the U-net architecture is used in [13].

Methods

All the described algorithms use CNNs and are designed to localize ICH in brain CT scans. Besides, the first two methods also classify the type of hemorrhage. Input data are adjusted by contrast transformation according to three standard radiological windows: bone, brain and subdural; hence, three input channels to networks are created.

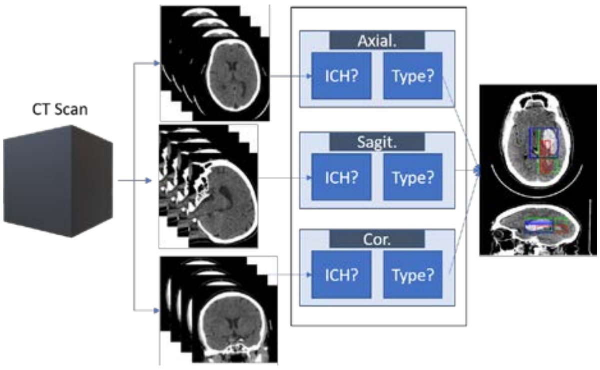

Fig. 1: Block diagram of the three subsystems (for axial, sagittal and coronal planes) of the proposed method based on 3D localization and classification. On the right, the output for multiple hemorrhages is shown: IPH (blue), IVH (red) and ground truth (green).

Experimental data

Head CT scans together with medical annotations were used from two publicly available databases: the CQ500 [6] and the RSNA [14]. As CQ500 has originally only patient-level annotations, they were extended by a non-medical expert to the level of labeling individual axial, sagittal and coronal slices. The “ground-truth” 3D BBs then result from the intersection of the perpendicular directions labeling. The classified 2D BBs for the CQ500 were obtained from the publicly available BHX extension [15].

Method based on 3D localization and classification

The algorithm [16] predicts 3D rectangular BB delimiting ICH in CT scans and also determines their types. It is based on the analysis of orthogonal 2D CT slices from mutually perpendicular anatomical planes (axial, sagittal and coronal).

Input CT scans are preprocessed by 3D rotational alignment from [17], and further resampled to a slice thickness of 5 mm in the axial direction. The proposed system consists of three independent subsystems (one for each plane), which are then composed of a series of CNN classification models. A block diagram of the system is shown in Fig. 1. The inputs of each subsystem are slices from a particular plane. The first classification CNN determines whether a slice is hemorrhagic or not. In case of a positive output, subsequently, the slice enters binary classification CNNs determining the probability of the presence of each single ICH type. To incorporate 3D information, the resulting predicted class

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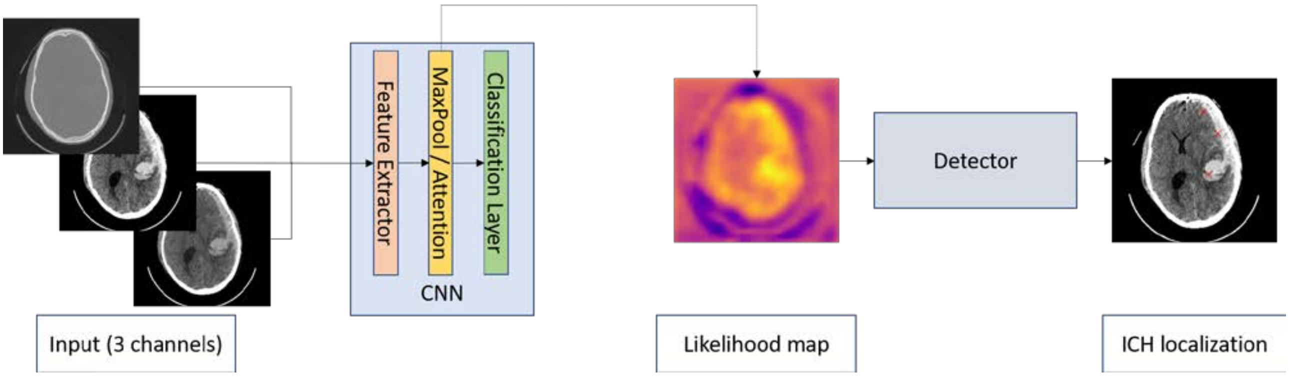

Fig. 2: Block diagram of the localization algorithm based on weakly-supervised learning. The output is in the form of highlighting the positions of the lesions.

for a particular slice is given by a weighted fusion of the predicted probabilities from the neighboring slices as well.

After classifying each slice from each plane, the final three-dimensional labeled BBs are given by the intersection of the outputs for each direction.

Detection networks for localization and classification

In [18], two methods were proposed and compared using known detection networks for localizing ICH in 2D axial slices along with determining the type of hemorrhage. The prediction of labeled 2D BB is performed by two architectures: Faster R-CNN [19] and YOLO v2 [20].

Both networks work in real time and consist of a feature extractor and a detection part. Faster R-CNN uses a so-called region proposal network, whose task is to suggest potential regions of searched objects from the feature space. The proposed regions are then fine-tuned and classified [19]. On the other hand, YOLO v2 is a single neural network that splits the input image into parts and then predicts the BBs and their classes [20].

Weakly-supervised learning-based method

The algorithm [21] works with 2D axial slices of the CT scan and determines the positional coordinates of each bleeding location. The goal was to create a CNN-based detector using data with classification annotations (i.e., the positions of the ICHs in the slices were unknown).

The CNN classification model was trained to predict the probability of ICH presence in a slice and simultaneously a heat-map denoting the likelihood of ICH's presence at specific image positions. In addition, a detector of local maxima in the map was created to provide positional coordinates of individual lesions. A block diagram of the algorithm is shown in Fig. 2.

The generation of the likelihood map is provided either by the feature extractor itself (which is subsequently followed by a global max-pooling layer) or by the so-called "attention" layer [22]. The detector then finds local maxima in the map with a value higher than a specified threshold and with a minimum distance from each other. To suppress irrelevant positions, an h-maxima transformation is performed.

Results

The CQ500 dataset was used for training and testing both the 3D localization method and the detection networks. Extended slice-level annotations were used for training the series of classifiers in the case of 3D method, on the other hand, BBs from BHX were used in the case of the standard detection networks. The RSNA data was used for training the models using weakly supervised learning. The method testing was performed on CQ500 with 2D BB annotations from BHX.

The results of the mentioned methods (or their variants) are shown in Table 1. The sensitivity (Se) and positive predictive value (PPV) overall for localization of all types of hemorrhages (i.e., without determining the type) are evaluated.

Table 1: The results achieved by the described methods. WS (MaxPool) denotes the weakly-supervised learning-based method in the variant of using a global max-pooling layer, WS (Att) represents the variant with an attention layer. Sensitivity (Se) and positive predictive value (PPV) are assessed overall for all ICH types.

Method	Se (%)	PPV (%)
3D Localization	57.3	77.1
Faster R-CNN	69.1	76.5
YOLO v2	57.3	69.9
WS (MaxPool)	57.72	61.88
WS (Att)	62.13	47.30

To interpret and compare performance of proposed algorithms, different types of output need to be

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considered. The true positive result of methods with BB-type output is given by a minimum Jaccard coefficient of 40% between predicted and annotated BB. In the case of centroid coordinates prediction, the result is correct as long as it is within the annotated BB. For further details on testing and statistical evaluation of the methods performance, see the original articles.

In terms of computational complexity, the 3D localization method requires the most memory and computational time (about 2 minutes per patient). The remaining methods are fairly faster in processing 2D slices (at a most on the order of seconds per slice).

Discussion

In comparison to classification- or segmentation-based methods, localization seems to be adequate in terms of providing not only information about the presence of pathologies, but also about their precise positions at the cost of relatively low time requirements for creating annotations.

Despite the high variability in the shape, position and size of ICH (even within a single type), the above-mentioned methods can localize the hemorrhage in the image. The advantage of the algorithms is the possibility of localizing multiple simultaneous lesions, and in the case of the output in the form of a BB, also their classification with the exception of EDH. This type was excluded from the statistics in the case of the method based on 3D localization and detection networks due to the insufficient amount of data in the database (13 scans in total).

2D localization has some advantage over 3D BB, since the radiologist views the image primarily in the axial direction and 2D methods allow more accurate localization in slices showing the top and bottom margins of a single bleeding (In 3D, the BB has a size determined by the maximum diameter of a particular lesion).

The advantage of the weakly-supervised learning-based method, in addition to the accurate determination of the positions, lies in the generation of likelihood maps that carry information about the degree of suspected ICH occurrence possibility at particular positions.

Despite the possibility of false results, the proposed methods have a high potential in the field of ICH diagnosis as they can minimize the probability of missing a bleeding by directly highlighting its position. In addition, incorporating the algorithm into a computer aided diagnosis system can significantly reduce the time required for patient evaluation.

Other possibilities of head CT data analysis

Modern deep learning methods can process a large amount of information at once, which gives them the potential to efficiently solve some challenging tasks for humans. Further opportunities for ICH localization lie in the reduction of false positives in some uncertain findings encountered by radiologists. Examples of such bypassing include refining localization in areas frequently affected by artifacts, differentiating ICH from calcifications or hypercellular tumors.

Some ICHs often occur as a result of skull fractures, and therefore a joint analysis of these diseases seems to have great potential, as the problem of localizing fractures and differentiating them from skull sutures is not trivial.

A planned extension of the project is the analysis of acute ischemic stroke. The use of modern algorithms for the analysis of non-contrast CT images, where the disease is not sufficiently distinct for humans, might be examined, as such imaging usually precedes further post-contrast scanning. The eventual successful recognition and analysis of the disease in the native-phase image could significantly reduce the diagnostic time or reduce the radiation burden on the patient.

Conclusion

Non-contrast CT is the imaging method of first choice in suspected cerebral circulatory disorders and an automatic CT image analysis may lead to a more efficient diagnostic process. Deep learning-based localization approaches have a great potential in computed aided diagnostics due to their ability to provide information about precise position of a lesion while not requiring too time-consuming annotation process. Localization methods predicting output for individual axial slices seem more convenient for radiologists (in comparison to 3D BBs), as they provide more accurate information on the position and size of the blood present in the particular slice (especially in the margins of lesions). Besides, they imitate the standard process of manual scan evaluation. Weakly supervised approach might be highly beneficial, as positional annotation may be totally omitted and not only the deterministic positional information is provided, but also likelihood maps giving valuable parallel information to individual axial CT slices.

Despite relatively low results, any of the localization methods can be a great stepping stone for developing a system that might make the process of diagnosis more efficient and precise.

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