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Intracranial Brain Haemorrhage Segmentation and Classification

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Abstract - Traumatic brain injuries are categorized as sudden damage to the brain which may be caused by a blow to the head. A traumatic brain injury can cause intracranial bleeding which may lead to Intracranial hemorrhage (ICH). Computerized Tomography (CT) scans are widely used by radiologists in the detection and diagnosis of ICH. A CT scan creates images of the brain which can help detect bleeding and other signs of trauma to the head. However, accurate detection and diagnosis of ICH depend on access to an experienced radiologist. Failure to accurately detect and treat ICH promptly can lead to disability or even death. This project aims to develop an artificially intelligent system capable of detecting, diagnosing ICH, and classifying its sub-types. For this purpose, we will employ the techniques of computer vision and machine learning to train a Fully Convolutional Network (FCN) called u-net on a publicly available data set of head CT scans. The development process will include taking CT scans as input, using u-net as an FCN to perform semantic segmentation to classify the type of ICH, and the region of the brain affected by it. The proposed system will facilitate junior doctors and radiologists by providing them with assistance in the detection of ICH and its subtypes.

Keywords: Classification, Detection, Faster R-CNN, FCN, ICH, Segmentation, U-NET

INTRODUCTION

In Pakistan, a road traffic injury surveillance study showed that nearly a third of the patients suffered from Traumatic Brain Injury (TBI), while 10% of these cases had moderate to severe TBI (Bhatti, Stevens, Mir, Hyder, & Razzak, 2015). A serious consequence of TBI is known as Intracranial Brain Hemorrhage (ICH). It occurs when a blood vessel ruptures or leaks due to a blow to the head and depending on its location in the brain it can be classified into five different types such as Subdural Hemorrhage (SDH), Subarachnoid Hemorrhage (SAH), Epidural Hemorrhage (EDH), Intraparenchymal Hemorrhage (IPH) and Intraventricular Hemorrhage (IVH) (P. Perel, Bouamra, Woodford, Mooney, & Lecky, 2009). Other causes of ICH include high blood pressure, fatty deposits in arteries, smoking, etc. (Cleveland Clinic, 2020). ICH is considered to be clinically dangerous as it can lead to paralysis or even death if not treated on time (Hssayeni et al., 2020).

Unenhanced Computerized Tomography (CT) scans are commonly used to analyze ICH as the X-ray attenuation and location of ICH on unenhanced CT scans make them detectable and allow radiologists to differentiate between the different types of ICH based on their location and identify potentially life-threatening hemorrhage to help make clinical decisions such as whether surgery is needed (Majumdar, Brattain, Telfer, Farris, & J. Scalera, 2018). However, in developing countries such as Pakistan, a majority of the population does not have access to expert radiologists for immediate diagnosis which leads to a higher mortality rate.

Developments in Deep Learning algorithms such as convolutional neural networks have greatly influenced fields such as classification and segmentation and have provided various data models to achieve these tasks. Furthermore, fully convolutional networks (FCN) architectures such as U-net (Ronneberger et al. 2015) are widely used for biomedical image segmentation and have outperformed any prior methods. Thus, these deep learning algorithms can be used to facilitate the detection of ICH to those who do not have immediate access to neuroradiologists. However, very little work

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has been done on segmenting and classifying ICH from a given CT scan. (Majumdar, Brattain, Telfer, Farris, & J. Scalera, 2018) (Hssayeni, et al., 2020).
Our research will be focused on developing an interface that can take as input, a CT scan, and using an FCN architecture we can segment the area to detect as well as classify the type of ICH detected. Our interface can be used to assist junior radiologists in detecting ICH in case expert neuroradiologists are not readily available.

LITERATURE REVIEW

The research work elaborated below has been carefully selected, as such, to focus on various deep learning and traditional techniques and methodologies used for the detection of TBI and ICH.
The literature, furthermore, focuses on segmentation, extraction, and classification of brain features to effectively detect the presence of ICH (and its subtypes) or TBI. The segmentation is done using different techniques including but not restricted to; CNN, FCN, Mask R-CNN, Faster R-CNN, and PatchFCN. The related work has been grouped according to the used techniques.
The first step to detect the presence of an ICH in any given slice would be to train a binary classifier model to output a 0 (not detected) or 1 (detected) label so that the given CT slice can be forwarded to other units to be processed. For this, several machine learning along with deep learning techniques were explored. For the machine learning techniques, algorithms such as SVM and Logistic Regression, and for deep learning techniques, a simple CNN was explored for feature extraction and classification.
The presence of ICH and its subtypes, generally, can be achieved in several ways. FCNs provide pixel-level details to detect and predict ICH. Many FCN models have been developed and used in the past for this purpose including dilated residual net (DLN), Modified VGG16. (Hssayeni, et al., 2020; Mahmood et al., 2014). used u-net to segment the ICH regions from the CT scans. In that, the CT scan was segmented into slices. Then each slice, divided into 16 windows, was given as input to the model. The ICH regions were delineated and saved as JPG images of 650 x 650. Also, gray-scale 650 x 650 masks for all CT slices were saved for two windows (brain window and bone window). FCN is primarily used for semantic segmentation. The effectiveness of FCN models varies by the size of the datasets. It was found that u-net performed with greater effectiveness as opposed to the aforementioned FCN models due to a smaller sized dataset (84 subjects). Hence, u-net was shown to be effective on smaller datasets. The study, therefore, uses u-net as the primary source of ICH segmentation. The network used 24 convolutional layers, four max-pooling layers, four up sampling layers, and four concatenations. The architecture is linear – containing a contracting and an expansive path. A sigmoid activation layer (contrary to SoftMax) is used to predict the ICH probability in each pixel.
It should be noted that before applying the u-net segmentation no pre-processing is applied on the original CT Scan slices other than removing 10 pixels (for border removal) resulting in 640 x 640 images. Three experiments were performed using varying inputs to u-net. First, using a grid search. Second, that supplied a full 640 x 640 slices – although it was expected to be biased towards the negative class as most pixels belonged to the positive class in each scan. The third, which was done to overcome the limitation of the second test, divided the slices in a 160 x 160 window with S=80 (stride). The resultant, segmented windows were then combined to produce a full image. To evaluate and compare, the Jaccard index and dice index was used to see how the segmented models match with the ground-truth segmentation.

$$\text{JaccardIndex} = |RICH \cap R\hat{\ } ICH|\ |RICH \cup R\hat{\ } ICH| \quad (1)$$
$$\text{Dice} = 2|RICH \cap R\hat{\ } ICH|\ |RICH| + |R\hat{\ } ICH| \quad (2)$$

Generally, U-Net is used for semantic segmentation, whereas Mask R-CNN is used for instance segmentation (Draelos, 2020).
Semantic segmentation assigns an object category label to each pixel in an input image. Thus, all similar objects come under the same label. Instance segmentation, however, assigns a distinct, individual label to each pixel in an input image. U-net introduces a semantic segmentation architecture. It is a type of a Convolutional Neural Network (CNN), also referred to as Fully Convolutional Network (FCN). FCN is a network that does not contain any Dense layers (as in usual traditional CNNs) instead it contains 1x1 convolutions that perform the task of fully connected layers (Dense layers). U-Net, given an input image, creates a binary mask of 1s and 0s (1 representing an object, 0 representing the background). Initially, the obtained binary segmentation mask will have problems. However, the u-net loss function compares the obtained binary masks with the ground-truth mask, to obtain a better segmentation in the next training iteration. The basic working of u-net focuses on obtaining a lower-dimensional image representation of image through CNN and subsequently performing up sampling on that low-dimensional image to produce a final output segmentation map. The lower-dimensional representation is a contracting path – a traditional CNN. The up-sampled image representation is an

expansive path. The outputs we obtain from u-net may be considered as raw output, thus, a function (either SoftMax or sigmoid) is needed to convert the raw values into probabilities.

The softmax function is:

$$P_k(x) = \frac{exp(a_k(x))}{\sum_{k'=1}^{K} exp(a_{k'}(x))} \quad (3)$$

In (3) a_k (x)is the activation in feature channel k at the pixel position x and K is the number of classes.

One of the most important aspects of u-net is data augmentation. In general, Datasets are small as it is a time-consuming process because there is a need to create ground truth segmentations. Thus, random rotations, shifts, grey-value variations as well as elastic deformations are applied to the test images.

An integral part of our study is to help us effectively locate and identify any type of ICH from a given brain CT scan. In object detection algorithms, bounding boxes are drawn to locate the region of interest (ROI). However, this cannot be achieved with a simple convolutional neural network as the output layers are fixed thus a framework such as Faster R-CNN was explored. For Faster R-CNN we use VGG and a feature extraction model which outputs a convolutional feature map that has all information regarding the image encoded (Faster R-CNN: Down the rabbit hole of modern object detection, 2018). An RPN then takes this processed image and outputs a set of rectangular objects along with an objectiveness score. For training RPNs a binary label is assigned to each anchor. A positive label is assigned if the anchors have the highest Intersection-over-union (IoU) score which is an overlap score with any ground-truth boxes or if the IoU overlap is higher than 0.7. A negative label is assigned if the IoU score is less than 0.3. RPN is implemented as an FCN and can be trained using back-propagation and stochastic gradient descent (Faster R-CNN: Down the rabbit hole of modern object detection, 2018).

Once the RPN model is run over our image, we have object regions with no class labels assigned to them. Fixed-size feature maps are extracted from each region and input to the Fast R-CNN to classify them accordingly. Faster R-CNN trains the RPN and Fast R-CNN independently after which the layers are joined using a detector network to initialize RPN training, and layers unique to RPN are fine-tuned. After which the Fully connected layers of Fast R-CNN are fine-tuned and both networks share the same convolutional layers and the network is merged to operate as one unit (Ren, He, Girshick, & Sun, 2017).

Lastly, the study (Ye, et al., 2019) evaluated the behavior of an advanced three-dimensional joint convolutional and recurrent neural network (CNN-RNN) for the detection of intracranial hemorrhage and five of its subtypes: cerebral parenchymal hemorrhage, intraventricular hemorrhage, subdural hemorrhage, epidural hemorrhage, and subarachnoid hemorrhage. The system was developed using a fairly large size of datasets that were collected from various centers with a diverse set of CT scanners. It integrated CNN and RNN to simulate the behavior of interpretation of the CT scans as carried out by radiologists. CNN was applied for feature extraction from slices of images and RNN was implemented for the inter-slice dependency context. Two levels of annotation details were allowed for training: 1) when ground truths of the subjects were available and 2) when ground truths for each slice in the scan were accessible. The CNN component focuses on extracting useful features from image slices. The RNN component makes use of these features and generates the probability of ICH or a subtype. We split the entire subjects randomly into training (80%), validation (10%), and testing set (10%). Training for ICH detection and its subtypes was performed under two settings, Sub-Lab and Sli-Lab.

Proposed Model

In this paper, we detect ICH from CT scans. The first step is to take 3D CT scan images and slice them into 2D images. These images are then fed to a binary classifier. In this paper, we use the SVM model which outputs 1 for ICH detected or 0 for ICH not detected in the given slice. On the instance of a 0, the CT slice will be discarded. The slices where SVM identifies an ICH (1 label) will then be input to our faster R-CNN model which will accurately detect the area the ICH is detected and classify the type detected.

This was followed by the implementation of VGG architecture, and RPN (Regional Proposal Network). Binary masks are converted into annotations – to be passed to Faster R-CNN as input. An RPN, with a classifier and a regressor, obtains a feature map from a pre-trained CNN-model (VGG). Faster R-CNN passes the original image to the pre-trained model. The obtained feature map is considered as an anchor. For training, we take all the anchors and put them into two different categories. Those that overlap a ground-truth object with an Intersection over Union (IoU) bigger than 0.5 are considered "foreground" and those that don't overlap any ground truth object or have less than 0.1 IoU with ground-truth objects are considered "background". At this point, ROI pooling is also used for proposed ROIs. Lastly, the SoftMax function is used for classification and linear regression for bounding boxes location.

The next stage is the usage of u-net to perform segmentation. The image is passed to u-net, an FCN, and if ICH is detected – a segmented region of the detected ICH is obtained and shown as a box surrounding the detected ICH region. The system is implemented by integrating different modules for Detection, Classification, and Segmentation to construct a unified system that will be able to assist junior radiologists in accurately identifying and locating the region where ICH is detected.

A CT slice is given as input to the system after which appropriate pre-processing is applied to our CT slice. Once the pre-processing phase is complete, the image is forwarded to the SVM model to identify whether an ICH is present in the slice through a 0/1 output. After that, the slices with no ICH detected are discarded while slices with ICH detected are forwarded to the detection and classification module which is implemented using Faster-RCNN where a bounding box is detected where ICH is located and the classifier classifies the type of ICH region in detected region. Once the ICH is detected, the given bounding box is input to our Fully Connected Network u-net to accurately segment the exact boundary where the ICH was located. Since the system is to be deployed as a standalone application, it will not be requiring internet access to operate. However, it will be requiring access to the systems file explorer for the user to upload CT scan images. Interactions with the systems file explorer can be achieved using permissions in JDK with the user providing explicit access to the software trying to access the system resource.

RESULTS

Experimental Setup

We used the CT Images for ICH detection and segmentation (Hssayeni, 2020) as the dataset. The obtained CT-scans were in 3D. The dataset has 82 CT scans out of which 36 scans are those of ICH patients. Each 3D image is sliced into 30 slices to get a larger 2D dataset. Slicing is done using the ImageIO library in Python. Once we have the 2D dataset, it is used to train 3 classifiers. We use SVM, Logistic Regression, and CNN as binary classifiers to detect the presence or absence of ICH.

Detection of ICH

We used 3 classifiers to detect ICH in 2D slices of CT scans. The results obtained by each classifier are given in table 1. We evaluated all three models based on precision, recall, and F1-score to determine a model that is the most suitable. The best performance is shown in bold.

Table 1: Performance of CNN, SVM and logistic regression in detecting ICH is 2D slices of CT scans.

	Precision	**Recall**	**F1-score**
CNN	0.81	0.74	0.70
SVM	**0.95**	**0.94**	**0.95**
Logistic Regression	0.85	0.85	0.85

From Table 1, we can observe that SVM performs the best out of all the algorithms on all three metrics defined. Thus, our choice for our binary classifier would be our SVM model.

CONCLUSION AND FUTURE WORK

The timely detection of ICH and any of its subtype(s) can serve as a potential life saver. The first phase of the research required collecting sample CT-scans of the brain (including the skull). A total of 84 test subjects were used, with each CT-scan divided into slices. These scans were the basis of the training for the deep learning model used. In addition, the scans required little to no pre-processing before being used.

There was a potential choice between the most appropriate deep learning model that was to be used to perform detection and segmentation. U-Net, an FCN, was found to be the most effective and efficient on smaller datasets to perform semantic segmentation and thus, it fit the requirements well. It was also considered to be more accurate than other proposed methodologies. There was a considerable debate between using Mask R-CNN and Faster R-CNN for instance segmentation. Faster R-CNN, which uses RPN, was given preference as the added functionality of Mask R-CNN was not required. The combination of the aforementioned deep learning models assisted in feature extraction.

Thus, our research has proposed a 3-phase architecture which includes a binary classifier (SVM) to discard any negative ICH slices, Faster R-CNN for accurate bounding box and class label prediction and U-net for segmentation.

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