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Deep Learning Models for Intracranial Hemorrhage Recognition: A comparative study

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Abstract

Every day, a large number of people with brain injury are received in the emergency rooms. Due to the large number of slices analyzed by the doctors for each patient and to accelerate the diagnosis, the development of a precise computer-aided diagnosis system becomes very recommended.
The aim of our work is developing a tool to help radiologists in the detection of intracranial hemorrhage (ICH) and its five (05) subtypes in computed tomography (CT) images. Five deep learning models are tested: ResNet50, VGG16, Xception, InceptionV3 and InceptionResNetV2. Before training these models, preprocessing operations are performed like normalization and windowing.
The experiments show that VGG-16 architecture provides the best performances. The model achieves an accuracy of 96%.

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Keywords: : Intracranial Hemorrhage; CT; Detection; Classification; Deep Learning; VGG-16.

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1. INTRODUCTION

Intracranial hemorrhage (ICH), which is a bleeding inside the skull, is a serious health problem requiring prompt and often intensive medical treatment. Intracranial hemorrhages account for about 10% of cerebrovascular accidents (strokes) in industrialized countries, where the stroke is the fifth leading cause of death [1]. There is five types of ICH: Subdural hemorrhage (SDH) located between the dura and the arachnoid, whereas the epidural subtype (EDH) involves bleeding between the dura and the bone. Intraparenchymal hemorrhage (IPH) is bleeding observed in the brain parenchyma area. intraventricular (IVH) is inside the ventricular system and subarachnoid hemorrhage (SAH) located in the subarachnoid space.

Identifying the location and type of any bleeding in CT images is a critical step in the patient's treatment. Diagnosis requires urgent intervention. When a patient is presented with acute neurological symptoms such as severe headaches or loss of consciousness, highly trained specialists examine medical images of the patient's brain to identify the presence, location, and type of bleeding [2]. The process is complicated and often time consuming.

In order to help physicians and radiologists save precious time, computer-aided diagnostic systems are developed to process images and detect the ICH.

In recent years, researchers focused their efforts on the development of deep learning approaches for image segmentation and classification. Many methods using deep learning models to detect the ICH have been published.

In [3] a convolutional neural network based on ResNet was built to detect ICH in CT images. The proposed model had an accuracy of 93.3%.

In [4], a series of deep convolutional neural networks have been proposed for classifying the 5 subtypes of intracranial hemorrhage. The CNN model is based on SE-ResNeXt50 and EfficientNet-B3. The proposed model reached a score of 0.0548 on the test set.

The authors in [5] proposed a hybrid architecture combining Double-Branch Convolutional Neural Network, Support Vector Machine, and Random Forest to detect ICH in CT images. They had an accuracy of 96.7% in intraventricular and 93.3% in intraparenchymal hemorrhages .

The authors in [6] proposed a novel three-dimensional (3D) combined convolutional and recurrent neural network (CNN-RNN) to detect ICH. The proposed model detects ICH and its subtypes with fast speed.

Togaçar et al. [7] proposed a hybrid model based on the AlexNet architecture, autoencoder, and the heat map method. The model achieved 98.6% accuracy, 98.1% sensitivity, and 99.0% specificity for detecting any hemorrhage using a dataset consisting of 2101 images with augmentation.

The aim of our work is to compare different CNN models. We have selected five models : ResNet50, VGG16, Xception, InceptionV3 and InceptionResNetV2. Before the implementation of the selected models, some preprocessing steps were performed.

The remaining of this paper is organized as follows: we dedicate the next section to the material and methods used in this paper. In section three we present the obtained results and we finish up with a conclusion.

2. MATERIALS AND METHODS

2.1. Convolutional Neural Networks (CNN)

LeNet-5 : is one of the most basic architectures. Consisting of 2 convolutional layers and 3 fully connected layers [8]. What we refer to now as "the pooling layer" was then called a down-sampling layer and had trainable weights (which is no longer the case in the design of CNNs). LeNet-5 has become the standard "model": stacking layers of convolutions and pooling and terminating the network with one or more layers fully connected. Its architecture has around 60,000 parameters.

VGGNet-16: This architecture designed by Simonyan and Zisserman researchers from the Visual Graphics Group in Oxford (hence the name VGG) was the second in the 2014 ILSVRC challenge, It was able to achieve an error rate of 7.3% in the top 5. The VGG-16 has 13 convolutional layers, 3 fully connected layers , and uses the ReLU activation function [9]. This network stacks more layers on AlexNet and uses smaller filters (2×2 and 3×3). It consists of 138 million parameters and takes up around 500MB of storage space. A deeper variant, VGG-19 was also designed.

GoogleNet / Inception : The GoogleNet (or Inception Network) was the winner of the 2014 ILSVRC challenge, It was able to achieve an error rate of 6.7% in the top 5, which was roughly equal to the performance of the human level. The model was developed by Google, has 22 layers with 5 Million parameters and includes a smarter implementation of the original LeNet architecture [10]. This is based on the idea of the Inception module. The basic idea behind Inception modules is that instead of implementing convolutional layers of various hyperparameters in different layers, we do all the convolution together to produce a result containing matrices of all the filter operations together.

ResNet: Probably the most revolutionary development in the field of CNN architecture development, after AlexNet, happened with ResNet or Residual Networks. The revolutionary idea infused into this architecture was the "identity shortcut connection" which involves transferring the results of a few layers to some deeper layers thus skipping certain layers in between which helps the network to train efficiently over thousands of layers, without degrading long-term performance [11]

A deep 1001-layer ResNet-1001 achieved a 3.57% error rate in the top 5 of the 2015 ILSVRC Challenge (beating human-level performance on the dataset), therefore winning all the prizes of this challenge in the fields of classification, detection, and localization.

2.2. Data Sets

The image database used is available on the Kaggle platform, accessible directly in the cloud from a Kaggle Notebook, or for download at[12].

This database was provided by the Radiological Society of North America (RSNA) in collaboration with members of the American Society of Neuroradiology and MD.ai. It contains over 25,000 brain CT scans labelled by over 60 volunteers, providing exactly: 752,803 learning CT images and 121,232 test CT images. All images are in DICOM format with size 512x512.

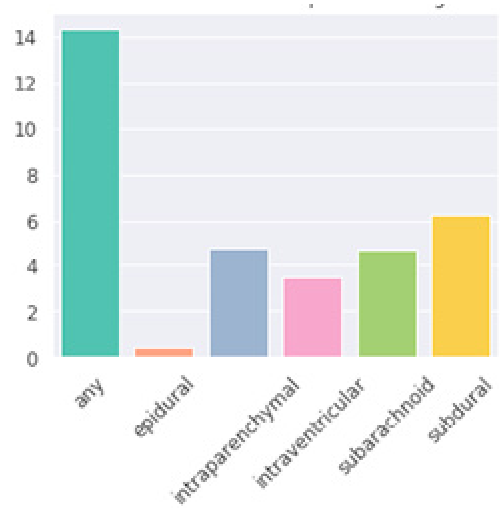


Fig.1. distribution of the positive cases

To carry out this work, we used a laptop computer with the following characteristics : Processor: Intel (R) Core (TM) i7-3630QM CPU @ 2.40GHZ, R.

The experiments were implemented on the Google Collaboratory platform and Kaggle Notebooks which provide a totally free GPU.

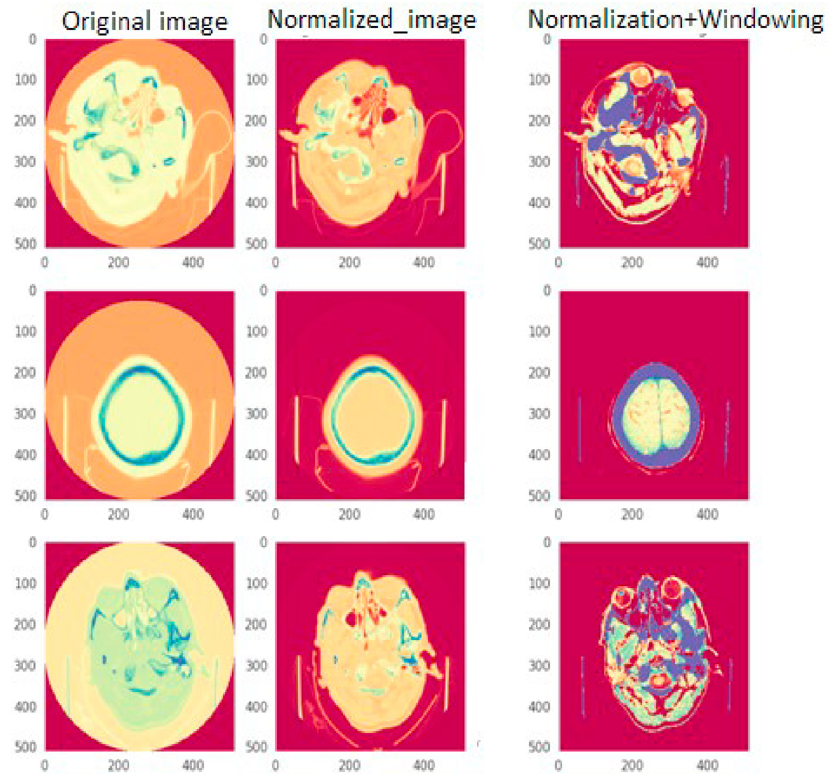
3. RESULTS

3.1. Pretreatment

Windowing: the choice of the centre and the width of the window of visualization is very important in CT acquisition. In a cerebral exam, to visualize the brain tissues, the radiologist chooses a window centre between 30 - 40 HUs and a width between 70-150 Hus.

In our work, after thorough examination of the different windows used in the acquisition of the data set, we chose a window with a centre of 30 and a width of 80.

In "Fig. 2", we present images before (raw image) and after different treatments (Normalization, windowing)



:

Fig. 2. Images before and after preprocessing

We note that :

- Raw images cannot be used directly for the diagnosis.
- After Normalization, the regions outside the skull have been assimilated to the air, so we can see an improvement in the quality of the images but the contrast is always low.
- After a windowing, the problem of contrast is solved, we can see the different brain tissues

"Fig. 3" shows six cases with HIC that we visualize after performing the various reprocessing operations which are normalization, filtering, and windowing. The type of bleeding present in the patient is mentioned above each picture.

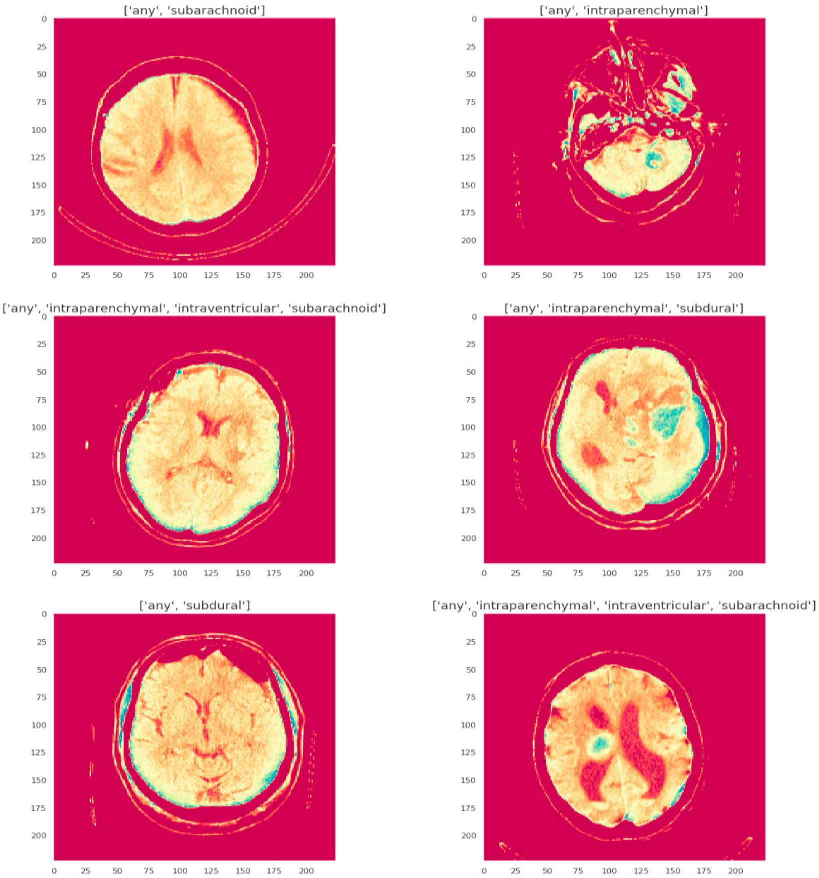


Fig. 3. Examples of the ICH types after windowing

From "Fig. 3" we notice that:

- The hemorrhage appears with the color blue which is in great contrast to the different tissues present around it, and therefore, it is easily detectable after performing our pretreatment.
- The type of bleeding is defined according to its location, shape, and proximity to other structures.
- A patient can have several types of bleeding at the same time.

3.2. Classification of ICH

We have chosen five CNN models : ResNet50, VGG16, Xception, InceptionV3 and InceptionResNetV2. After several experiments, we kept the following parameters : Batch_size = 16, optimizer function = Adam and learning rate (LR) = 0.001.

Table 1 summarizes the different results of accuracy and the loss function obtained with the five models:

Table 1 : Accuracy and the loss obtained with the five models

		ResNet50	VGG16	Xception	InceptionV3	InceptionResNetV2
MaxEpochs=10	Loss	0.24	0.23	0.25	0.24	0.22

	Accuracy	0.86	0.83	0.83	0.88	0.87
MaxEpochs=20	Loss	0.22	0.24	0.23	0.27	0.23
	Accuracy	0.88	0.94	0.87	0.91	0.89
MaxEpochs=30	Loss	0.23	0.22	0.23	0.24	0.25
	Accuracy	0.90	0.96	0.91	0.91	0.90

We observe a clear improvement in the performance of the five trained models with MaxEpochs = 30. The VGG16 model achieves an accuracy of 96%.

"Fig. 4" presents the confusion matrix of different ICH types obtained with the VGG16 model.

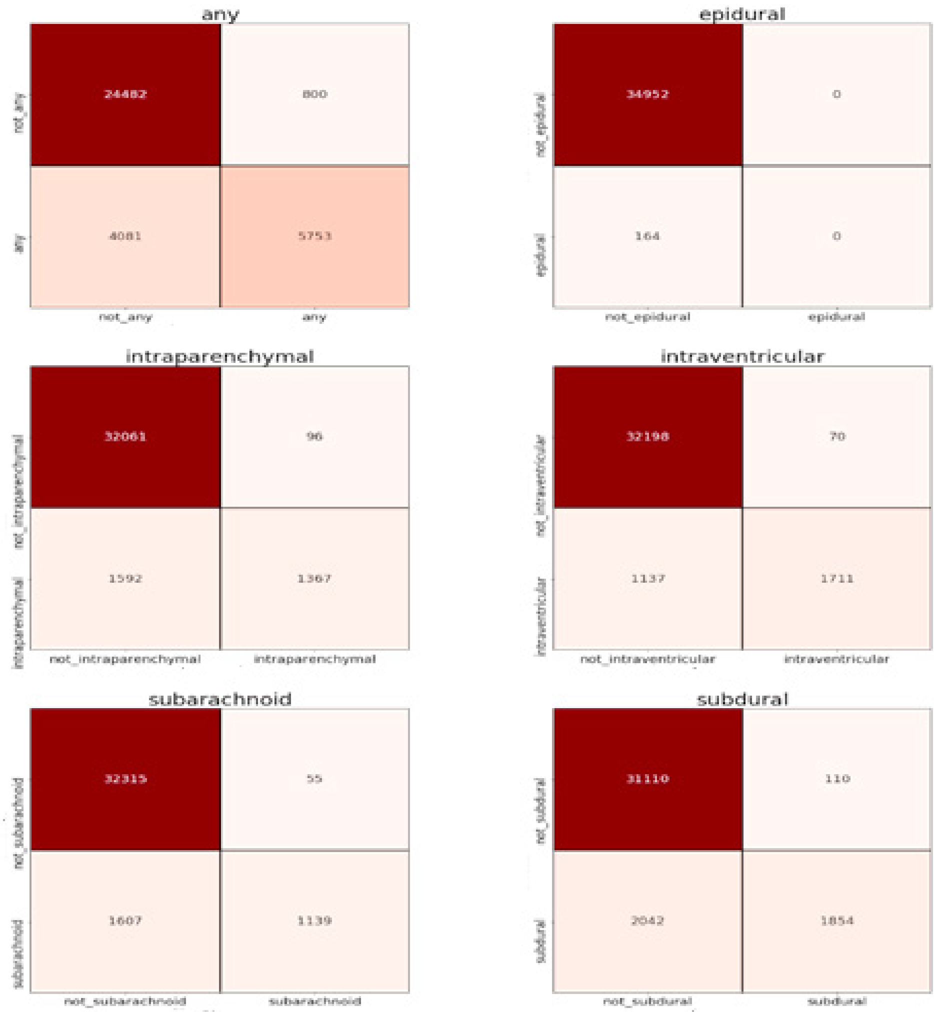


Fig.4. Confusion matrices for ICH subtypes

From “Fig. 4" we notice:

- The negative cases (TN) are well classified.
- For the 'intraparenchymal' subtype: our model was able to detect 1367 positive cases for this subtype and missed 96 cases by classifying them as negative (false negative FN).

- For the 'intraventricular' subtype: our model correctly detected 1711 positive cases and missed 70 positive cases.
- For the 'subarachnoid' subtype: our model was able to detect 1139 positive cases for this subtype and missed 55 cases by classifying them as negative (false negative FN).
- For the 'subdural' subtype: our model correctly detected 1854 positive cases and missed 110 positive cases.

4. Discussion

Many works based on deep learning models are proposed to detect the ICH in CT images. In [3] a Resnet model was implemented with an accuracy of 93.3%. In [4], a CNN model based on SE-ResNeXt50 and EfficientNet-B3 was proposed.

Another work published in [5] proposed a hybrid architecture combining Double-Branch Convolutional Neural Network, Support Vector Machine, and Random Forest to detect ICH in CT images. They had an accuracy of 96.7% in intraventricular and 93.3% in intraparenchymal hemorrhages.

Togaçar et al. [7] proposed a hybrid model based on the AlexNet architecture, autoencoder, and the heat map method. The model achieved 98.6% accuracy, 98.1% sensitivity, and 99.0% specificity for detecting any hemorrhage using a dataset consisting of 2101 images with augmentation.

In our work, we have implemented five models: ResNet50, VGG16, Xception, InceptionV3, and InceptionResNetV2. We have found that the VGG16 model provides the best accuracy (96%). We report in table 2 the sensitivity, negative predictive value (NPV), and F-score for the ICH sub-types.

We exclude the Epidural hemorrhage because for this type, we have only a few (<1%) positive occurrences. It will be difficult to form a model which is sufficiently robust and which does not tend to overfit.

Table 2 : Sensitivity, NPV and F-score for the ICH sub-types

	intraparenchymal	intraventricular	subarachnoid	subdural
Sensitivity	93.43	96.06	95.39	94.39
NPV	99.70	99.78	99.83	99.64
F-score	62.20	73.92	57.81	63.27

We see from table 2, that the intraventricular type have the best sensitivity (96.06%).

5. Conclusion

In this paper, a comparative study between five deep learning models was performed. The aim of this study is to identify the best architecture. Before the implementation, we have preprocessed the data set with normalization and windowing operations. The experiments show that the VGG16 model provides the best accuracy.

In future work, we proposed to use other preprocessing methods to improve the performances of the CNN models. We proposed also, to treat the problem of unbalanced data in case of the epidural hemorrhage due to the lack of positives cases in the dataset..

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