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ORIGINAL PAPER

Intracranial hemorrhage detection: how much can windowing, transfer learning and data augmentation affect a deep learning model's performance?

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Abstract

The application of Deep Neural Networks to detect intracranial hemorrhage from computed tomography images has been widely used in clinical medicine. In general, building these solutions combines three types of approaches: Preprocessing, Transfer Learning, and Data Augmentation. This study's goal was to measure the contribution of each of these approaches and thus highlight which approach has more margin of improvement. An experimental study was conducted on a public dataset containing computerized tomography images. The comparison used the stratified ten-fold cross-validation process to set confidence intervals evaluating performance measured by the area under the receiver operating characteristic curve. The ResNet-50 was the deep learning model selected. The results showed that all the approaches raise the generalization power when applied in isolation, and Data Augmentation offers the most significant gain to the baseline. The experiment also showed an opportunity to improve the detection of intracranial hemorrhage by applying new preprocessing techniques since this was the approach that showed the smallest increase in discriminatory power among the investigated approaches. The paired Wilcoxon's Signed-Rank Test showed that not all the differences were statistically significant, with a confidence level of 95%.

Keywords: Deep Learning; Data Augmentation; Intracranial Hemorrhage Detection; Transfer Learning; Windowing.

Resumo

A aplicação de Redes Neurais Profundas para detecção de hemorragia intracraniana a partir de imagens de tomografia computadorizada tem sido amplamente utilizada na medicina clínica. Em geral, a construção dessas soluções combina três tipos de abordagens: pré-processamento, transferência de aprendizado e aumento de dados. O objetivo deste estudo foi medir a contribuição de cada uma dessas abordagens e, assim, destacar qual abordagem tem mais margem de melhoria. Um estudo experimental foi realizado em um conjunto de dados público contendo imagens de tomografia computadorizada. A comparação foi realizada através do processo de validação cruzada estratificada, repetido 10 vezes para definir os intervalos de confiança para a avaliação de desempenho, medido pela área sob a curva *Receiver Operator Characteristic* (ROC). A ResNet-50 foi a rede de aprendizado profundo selecionada. Os resultados mostraram que todas as abordagens aumentam o poder de generalização quando aplicadas isoladamente, e o aumento de dados oferece o ganho mais significativo para a solução de base. O experimento também mostrou uma oportunidade de melhorar a detecção de hemorragia intracraniana por meio da aplicação de novas técnicas de pré-processamento, uma vez que essa foi a abordagem que apresentou o menor aumento no poder discriminatório entre as abordagens investigadas. O teste de hipótese Wilcoxon emparelhado mostrou que nem todas as diferenças foram estatisticamente significativas, com um nível de confiança de 95%.

Palavras-Chave: Aprendizado Profundo; Aumento de Dados; Detecção de Hemorragia Intracraniana; Transferência de Aprendizado; Windowing.

1 Introduction

The occurrence of bleeding in the interior of the cranium is denominated Intracranial Hemorrhage (ICH). They can be classified as Epidural hematoma, Subdural hematoma, Subarachnoid hemorrhage, and Intracerebral hemorrhage (Bruneau et al., 2002). It is a grievous injury, generally leading to severe incapacitation or death. Studies show that more than half of patients with intracerebral hemorrhage die after a year (Togha and Bakhtavar, 2004; Kuohn et al., 2020). The detection of ICH is done by imaging, and there are two types of imaging for the detection of ICH: Computerized Tomography (CT) and Magnetic Resonance (MR) (Balasooriya and Perera, 2012). MR is a versatile tool for *in vivo* exams due to the numerous contrast mechanisms that it offers. Its use is most appropriate in soft tissue imaging (Polzehl and Tabelow, 2019). MR's most significant disadvantage is the cost of its equipment (Ibrahim et al., 2012). Fig. 1 illustrates an MRI machine. CT leads the medical imaging field due to its excellent spatial resolution, capability to represent anatomic details with little ambiguity, and a more affordable cost (Samei and Pelc, 2020). In CT, a motorized x-ray source spins around the patient, and each time it completes a rotation, the computer processes the data and generates an image. Fig. 2 illustrates the CT equipment, and Fig. 3 shows a CT scan.

Figure 1: Magnetic Resonance Imaging Machine (*MRI*, n.d.)

Artificial Intelligence (AI)-assisted diagnosis systems have been widely used in clinical medicine, mainly with the application of Deep Neural Networks (DNN) (Lu et al., 2021). DNN can help detect diseases, significantly shorten the diagnosis time, and speed up the treatment process (Georgeanu et al., 2022). This study aimed to investigate the contribution of three essential steps in building a DNN solution for ICH detection.

The remainder of this paper is organized as follows. Section 2 presents the problem definition. Section 3 provides a brief presentation of Basic Concepts. Section 4 presents related works. Section 5 shows the experimental methodology. Section 6 presents the experimental results and their interpretation. Finally, Section 7 concludes this paper and proposes future works.

Figure 2: Modern CT Scan Machine (Al-Ameen and Sulong, 2016)

2 Problem Definition

The development of intracranial hemorrhage detection models using Deep Learning has grown over the last few years (Suzuki, 2017). This study focused on the presence of hemorrhage or not as a binary classification problem. There are three types of approaches widely used when building Deep Learning models:

- Preprocessing
- Transfer Learning
- Data Augmentation

This study investigated how each approach is applied in intracranial hemorrhage detection. More specifically, this work aimed to answer the following research question: **What is the gain of each approach in building Deep Learning models for intracranial hemorrhage detection?** The answer to this question is of great importance to this field, as it can point to which approach has more margin of improvement. Fig. 4 illustrates the investigated problem.

3 Background

3.1 Pre-Processing

The images generated by CT are in the DICOM (Digital Imaging and Communications in Medicine) format, which is the gold standard in the digital medical imaging field (Pereira et al., 2018). The DICOM images have a great variety of gray tones due to the attenuation of x-ray beams. This attenuation is proportional to the density of the tissue region, denominated "attenuation coefficient" and measured by Hounsfield Units (HU) (Pereira et al., 2018). This way, each pixel of a DICOM image possesses a value ranging from -1000 to 3000 in the HU scale (DenOtter and Schubert, 2022). Windowing and Multichannel are two

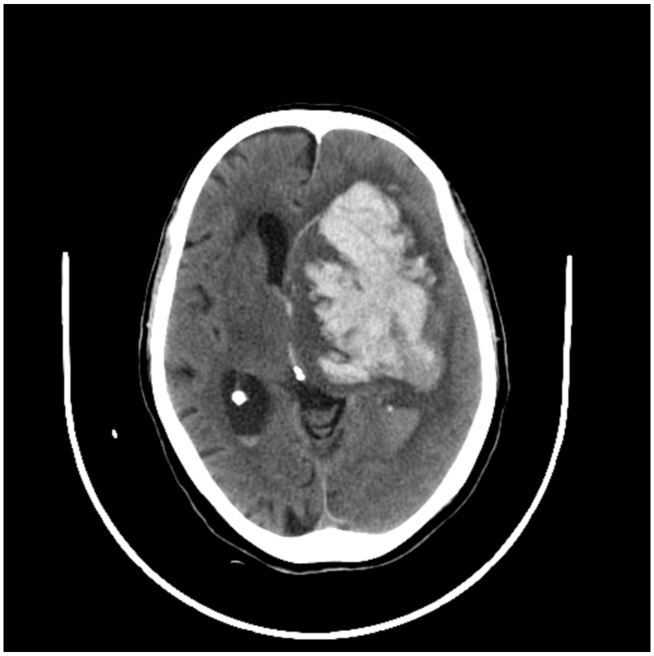

Figure 3: Slice from a head CT Scan (Chilamkurthy et al., 2018)

preprocessing techniques frequently used in CT scans that are in DICOM format.

3.1.1 *Windowing*

Windowing is a technique that modifies the HU scale of an image to highlight particular structures and generate a new image (Todsaporn et al., 2008). This technique has two parameters: Window Width (WW), which defines the interval of the Hounsfield scale in which the grayscale must extend, and Window Level (WL) used to centralize the gray scale (Tidwell, 1999). In the Intracranial Hemorrhage literature, the most popular windowing parameters are brain (wl = 40, ww = 80), bone (wl = 600, ww = 2800), and subdural (wl = 80, ww = 200). Fig. 5 shows an application of this technique.

3.1.2 *Multichannel*

The multichannel method is a preprocessing technique that builds a multichannel image from stacking single-channel images. This study uses multichannel to stack those three windowing parameters: brain, bone, and subdural.

3.2 Transfer Learning

Data acquisition is expensive in some domains, like bioinformatics; thus, there is a limited supply of training data (Hemphill et al., 2011). Transfer learning can solve the problem of insufficient training data by improving a learner from one domain with transferred information from a related domain (Weiss et al., 2016). Fig. 6 shows the learning process of transfer learning. In Deep Learning, one of the most popular transfer learning approaches is Fine-tune, which consists of using the weights from a

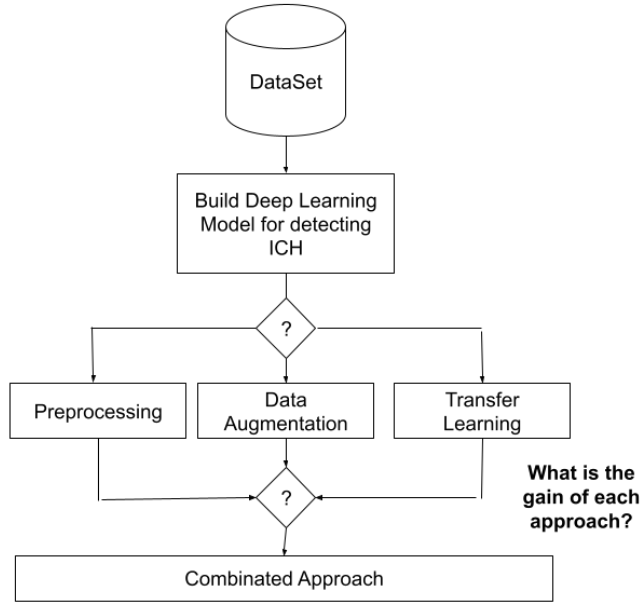

Figure 4: Problem Definition Diagram

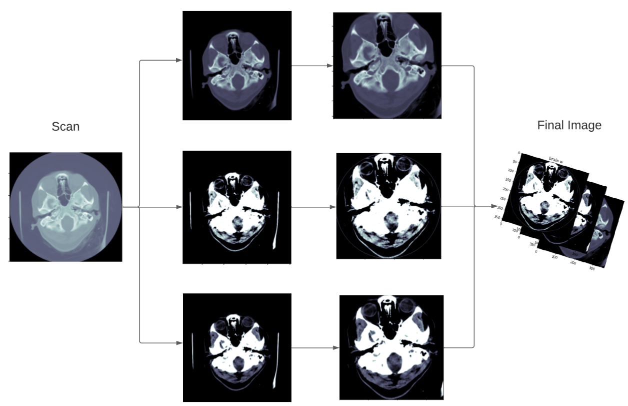

Figure 5: Multichannel Windowing

pre-trained network trained in a large-scale dataset of a source domain in the target domain. In this approach, a new network will be trained on a target domain by only modifying the weights of the final layers of the pre-trained network's architecture. The initial layers of the pre-trained model are frozen, and reused (Vrbančič and Podgorelec, 2020).

3.3 Data Augmentation

Data Augmentation is another approach used to deal with limited samples. It is a regularization strategy that artificially increases the number of training samples (Shorten and Khoshgoftaar, 2019). In image classification, there are numerous techniques of Data augmentation. The traditional techniques use affine transformations to

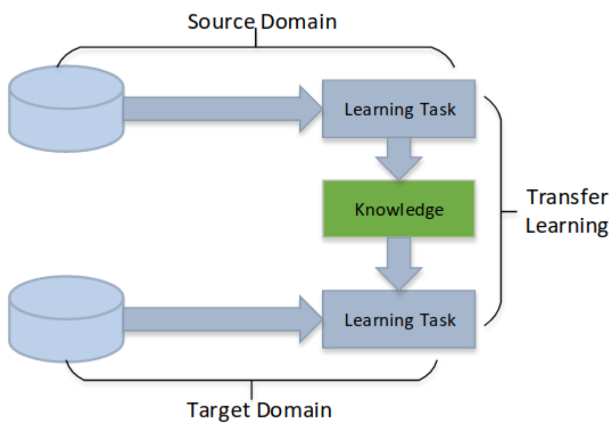

Figure 6: Learning process of transfer learning

manipulate the training data, such as cropping, rotating, and flipping (Nalepa et al., 2019). Fig. 7 shows these transformations. However, choosing which techniques to apply to be successful depends on domain knowledge and is further verified by testing performance (Neto et al., 2017).

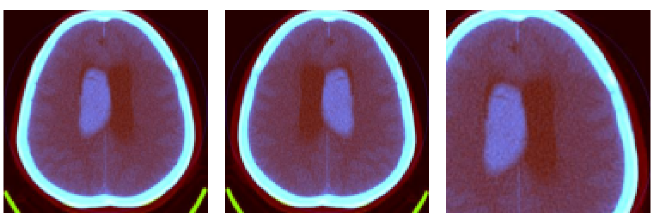

Figure 7: Traditional Transformations

4 Related Works

Brain imaging is a vast and growing field that has produced a significant amount of work. As an example, we can cite: (Nafees Ahmed and Prakasam, 2023) and (Gruschwitz et al., 2021). Nafees Ahmed and Prakasam (2023) studied multiple kinds of hemorrhage and aneurysm detection problems and developed machine and deep learning models to recognise them. They describe the many challenges of brain imaging, the specifics of some methods and their advantages. They conclude stating swiftness and accuracy are vital to this problem, and that AI can help expedite the process. But necessitates significant collaborative efforts to do so. Gruschwitz et al. (2021) evaluated the performance of a novel deep learning-based pipeline using a Dense U-net architecture for detection of ICH in unenhanced CT scans. The algorithm detected ICH with a sensitivity of 91.4% and overall accuracy of 91.0%. When paired with a radiologist a sensitivity of 100% was achieved. They conclude that deep learning applications have immense potential as triage tools and for additional reviews of manual reports. However, among the found research, the closest to this work are:

Chilamkurthy et al. (2018) built a hemorrhage detection solution and applied it to two datasets. They used ResNet18 with minor modifications, although they don't mention transferred learning. They used multichannel windowing as preprocessing, and their best results achieved AUC ROC 0.97. They didn't measure the impact of multichannel windowing preprocessing. They also don't use data augmentation.

Nalepa et al. (2019) compiles and presents an extensive and cohesive review of various data augmentation techniques focused on brain imaging, from simple affine transformations, such as rotation and flipping, to highly complex such as elastic transformations. They present the effects of these techniques in different models and studies from a broad range. They conclude that affine transformations are still the most widely used. They do not mention or measure the effects of preprocessing techniques or transferred learning.

Shorten and Khoshgoftaar (2019) presents a survey of different data augmentation techniques. They present this technique's effects on models such as AlexNet, VGG-16, ResNet, Inception-V3, and DenseNet. They also talk about transferred learning and how it can also help mitigate overfitting. They conclude that the methods discussed help mitigate overfitting without working with big data. They do not mention or measure the impact of preprocessing techniques. Nor do they measure the impact of transfer learning.

Zheng et al. (2018) compares preprocessing techniques for deep learning. They work with data gathered from sensors. Appling data segmentation and training four different models. Raw Plot, Multichannel, Spectrogram, Spectrogram & Shallow Features were the selected preprocessing techniques. The multichannel method presented the best results. They do not mention or measure the impact of data augmentation or transferred learning.

5 Methodology

An experimental study was carried out to measure the importance of preprocessing, transfer learning, and data augmentation in detecting ICH. We investigated eight approaches. The following labels will be used to refer to these approaches:

- **B**: Baseline;
- **W**: Windowing;
- **TL**: Transfer Learning;
- **DA**: Data Augmentation;
- **W + DA**: Windowing and Data Augmentation;
- **DA + TL**: Data Augmentation and Transfer Learning;
- **W + TL**: Windowing and Transfer Learning;
- **W + TL + DA**: Windowing, Transfer Learning and Data Augmentation;

We used ResNet50 as our Deep Learning model because it has been widely used in this area (He et al., 2015). To apply transfer learning, we used the set of weights from ImageNet (Deng et al., 2009).

The dataset used in the study contained 34999

CT scans[1]. The target variable has two classes: YES, indicating the presence of hemorrhage, and NO, indicating its absence. This dataset was made using data randomly selected from the RSNA Intracranial Hemorrhage Detection competition, organized by the Radiological Society of North America and made available by the KAGGLE platform (*RSNA Intracranial Hemorrhage Detection*, n.d.). The under-sampling was necessary because we performed this study on the free version of the Google Colab[2] platform, which has limited disk space and computational power. Since the dataset is unbalanced (YES=14% and NO=86%), we use the area under the receiver operating characteristic curve (AUC ROC) as the performance evaluation metric (Hajian-Tilaki, 2013). The comparison was performed using the stratified ten-fold cross-validation method to set the confidence interval (Purushotham and Tripathy, 2012).

5.1 Experiment Setup

All approaches used in this study have been implemented using the Keras framework, a common practice in the literature. ResNet's parameters influence its performance, so the parameters were chosen based on recommendations found in the literature. The recommendations used were: Masters and Luschi (2018) for BatchSize, Kingma and Ba (2014) for Learning Rate and Optimizer and Prechelt (2012) for Stop Criteria. Table 1 shows the parameters used.

Table 1: Used Parameters

Parameter	Value
BatchSize	64
Learning Rate	1.00E-05
Optimizer	Adam
Stop Criteria	Early Stopping

5.2 Hypothesis Test

In this work, the paired Wilcoxon's Signed-Rank Test was applied to verify if there is a difference between the mean of the solutions achieved by the two approaches. Statistical significance value $\alpha = 0.05$. The test setup used in this study was:

- **Null Hypothesis** : $\mu 1$ is equal to $\mu 2$
- **Alternative Hypothesis** : $\mu 1$ is different than $\mu 2$

Where

- $\mu 1$ is the mean of AUC ROC of one approach;
- $\mu 2$ is the mean of AUC ROC of another approach.

[1] https://github.com/amaropedro/IC-Detect_Hemorrhage
[2] https://colab.research.google.com/

Table 2: Medium AUC ROC Values

Label	Medium AUC ROC
B	0.787
TL	0.850
DA	0.879
DA+TL	0.907
W	0.801
W+TL	0.888
W+DA	0.866
W+TL+DA	0.915

6 Results

Fig. 8 shows the average gain obtained from each investigated approach in relation to the baseline, using the AUC ROC from ten-fold cross-validation as a metric. Table 2 shows each approach's average AUC ROC value. The results show that all the approaches raise the generalization power when applied in isolation. More specifically, Data Augmentation offers the most significant gain (11.69%), followed by Transferred Learning (8.01%) and Windowing (1.78%).

Data Augmentation and Transfer Learning outshine the rest when we analyze the results obtained from two approaches applied simultaneously. Finally, the results show that the best solution is applying the three approaches simultaneously, as it improved by 16.26% when compared to the baseline. Our results are consistent with several studies suggesting Preprocessing, Transfer Learning, and Data augmentation improves Deep Learning solutions (Balasooriya and Perera, 2012; Chilamkurthy et al., 2018; Nalepa et al., 2019; Weiss et al., 2016; Shorten and Khoshgoftaar, 2019; Zheng et al., 2018). However, we measured the contribution of each approach. With this information, we can glean that the preprocessing technique Windowing has the lowest contribution to the model. Table 3 shows the p-values obtained from the hypothesis test applied at each approach. As we can see, only three tests bore statistically insignificant differences, with 95% confidence (p-value < 0.05). The results show that applying Windowing in conjunction with the other two approaches does not improve the solution's generalization power, with 95% confidence, since the p-value of the hypothesis between W+TL+DA e TL+DA was 0.1141.

Fig. 9 shows a BoxPlot for the ten-fold cross-validation. As can be seen, the approach that produces more variance in the model is Windowing. A plausible explanation is that Windowing generates more diverse images from the original. The results show that there is an opportunity to improve the detection of ICH by applying new preprocessing techniques. A plausible explanation for this direction is that preprocessing techniques are more dependent on domain knowledge than Transfer Learning and Data Augmentation.

7 Conclusion

We measured the contribution of Windowing as preprocessing technique, Transfer Learning, and Data Augmentation in detecting intracranial hemorrhage

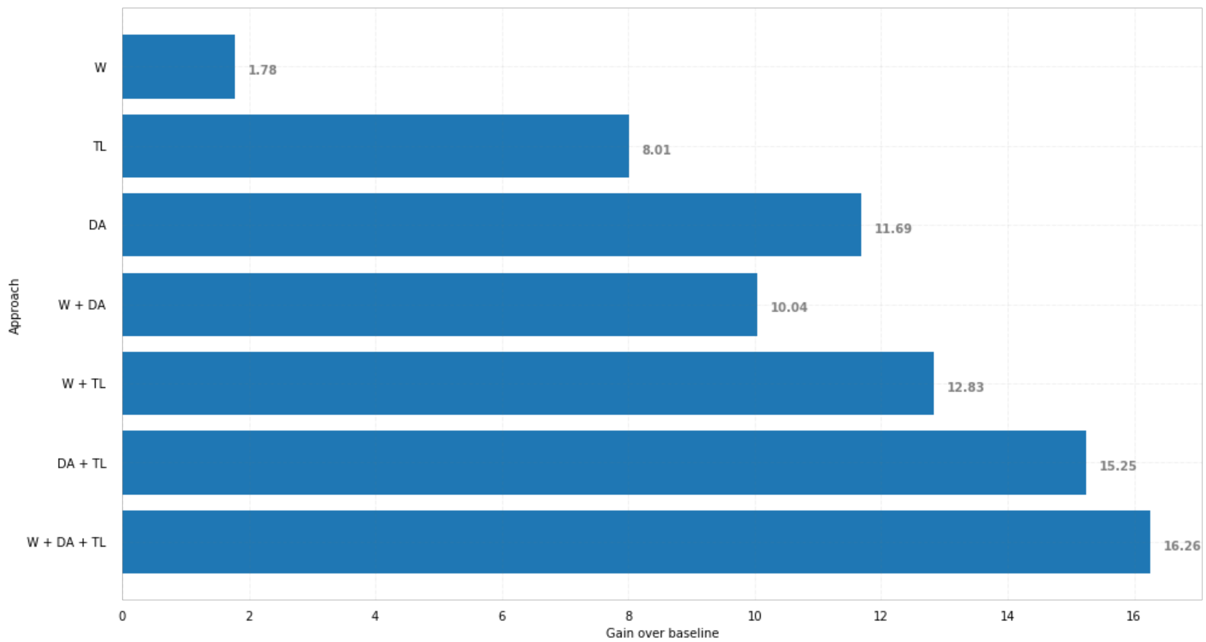

Figure 8: Medium Gain

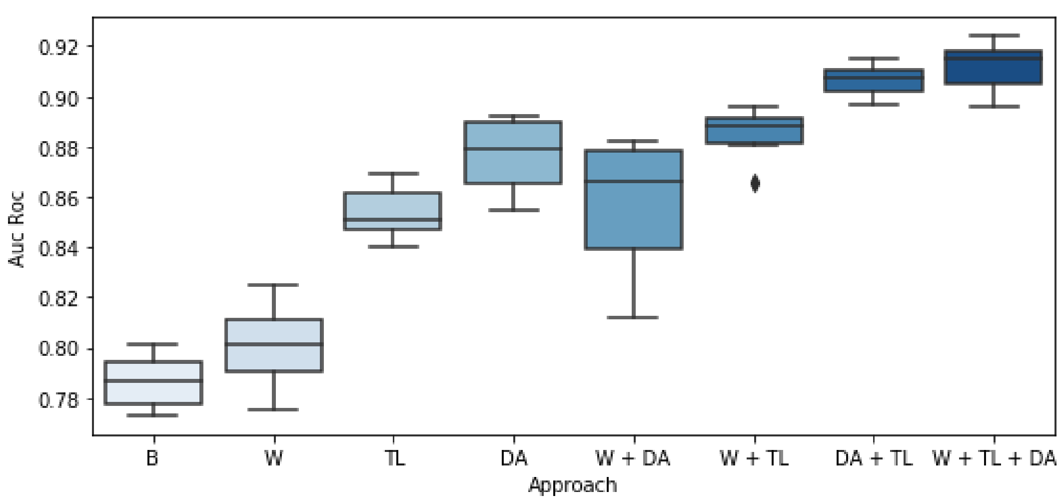

Figure 9: BoxPlot

Table 3: Critical values for post-hoc tests after the Kruskal-Wallis Test

	B	DA	DA+TL	TL	W	W + DA	W + TL
DA	0.005062	-	-	-	-	-	-
DA+TL	0.005062	0.005034	-	-	-	-	-
TL	0.005034	0.00691	0.005034	-	-	-	-
W	0.05917	0.005062	0.005034		-	-	-
W+DA	0.005034	0.04136	0.005034	**0.594**	0.005034	-	-
W+TL	0.005034	**0.09691**	0.005005	0.005062	0.005062	0.005034	-
W+TL+DA	0.005034	0.005034	**0.1141**	0.005062	0.005062	0.005062	0.005034

using Deep Learning. An experimental study was conducted on a public dataset containing computerized tomography images. The main conclusions that emerged from the present study were: 1) all the approaches raise the generalization power when applied in isolation; 2) Data Augmentation offers the biggest gain in relation to the baseline, followed by Transferred Learning and Windowing; 3) applying the three approaches simultaneously had the highest gain over baseline, however it was not statistically significant. Our results show an exciting opportunity to improve the detection of intracranial hemorrhage by applying new preprocessing techniques since this was the approach that showed the smallest increase in discriminatory power among the investigated approaches. As a future work, this study will be expanded to investigate different Windowing parameters and to apply other preprocessing techniques.

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