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Standardization of Baseline CT Images for Improving the Training of Automated Models

Código de la comunicación (07-011)

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1. Introduction

Early detection of stroke using non-contrast computed tomography (CT) is essential for prompt diagnosis and treatment. However, baseline CT images vary widely in voxel dimensions and acquisition parameters. To enable their use un convolutional networks, it is critical to standardize the input data. In this work, we applied a standard preprocessing pipeline based on commonly used medical imaging practices normalize voxel data and improve model performance. This approach is implemented in a simple and fully automatic way, without relying on segmentation masks or pretrained models.

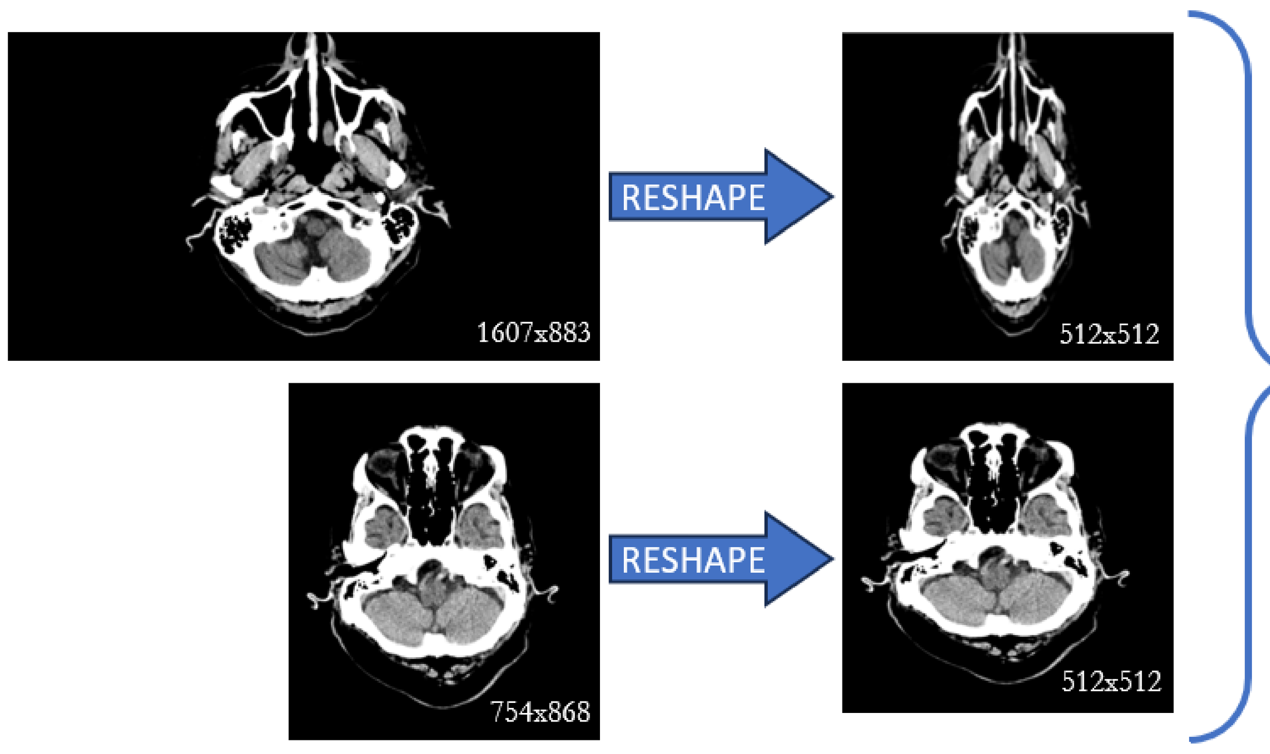

Figure 1. Need for standardization prior to reshaping

2. Methodology

The dataset comprises 635 non-contrast CT images from 56 patients, classified into two groups: Stroke and Non-Stroke. Although the images were acquired at the same clinical center, they exhibited significant heterogeneity in voxel dimensions and acquisition formats which can introduce biases and incompatibilities when training convolutional neural networks.

Diagnose	Total Images	Total Patients
Stroke	503	25
No Stroke	132	31

Table 1. Data description

To address this, we applied a standard preprocessing pipeline based on commonly accepted practices in medical imaging. This includes an automatic cropping algorithm that identifies the region of interest (ROI) by detecting non-zero voxels, leveraging the consistent black background typical of non-contrast CT scans. This method allows for a fully automated ROI extraction without relying on segmentation masks or pretrained models.

Following cropping, black-padding is applied to form square images, which are then rescaled to a fixed input size (512×512). This process preserves anatomical proportions and avoids spatial distortions. All images are converted to grayscale, as color information is not relevant in this context.

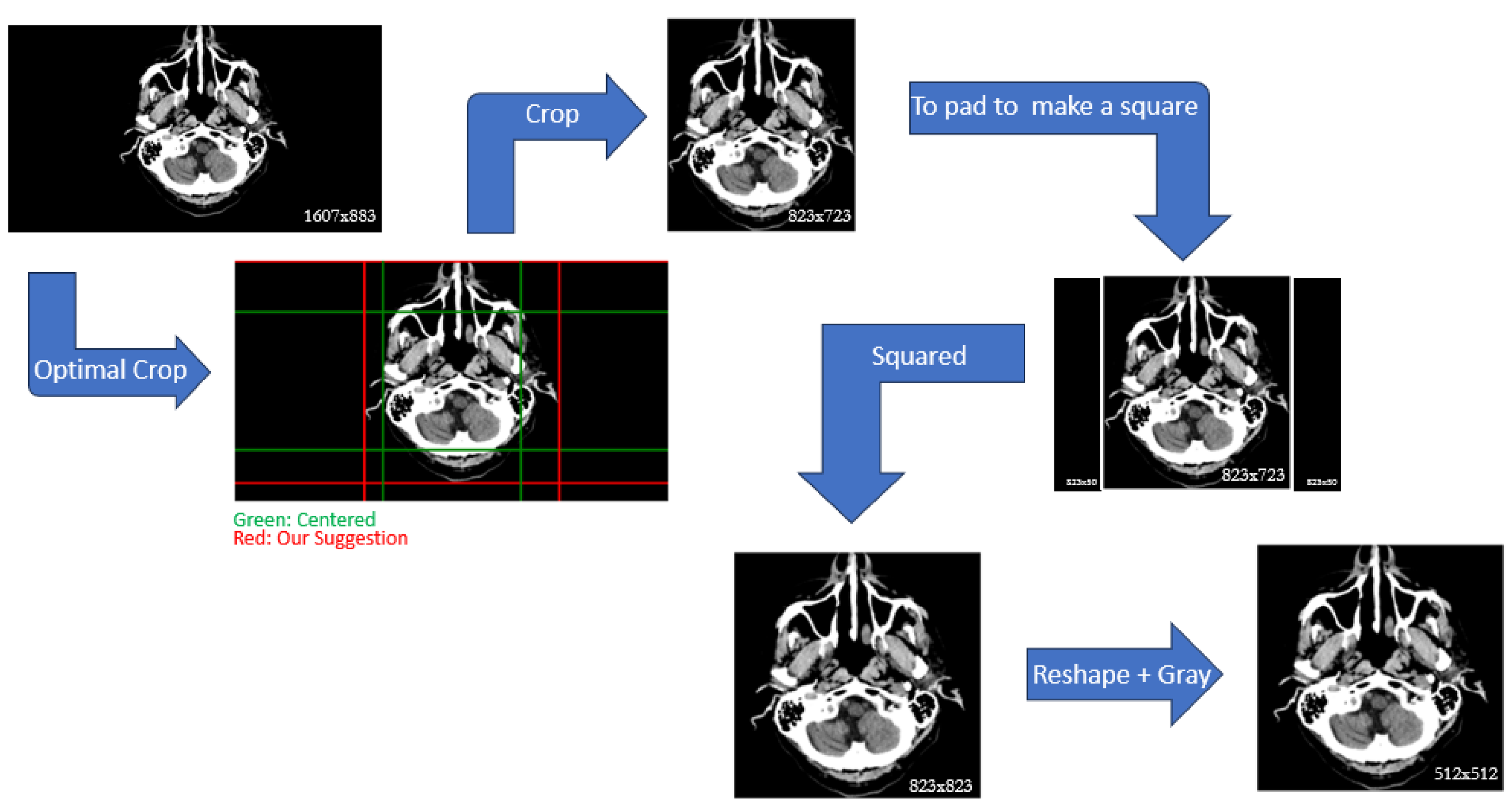

Figure 2. Crop Algorithm

In line with literature standards, we also applied data augmentation techniques to enhance variability and improve model generalization. These include:

Random rotations (±45°)
Vertical flipping
Contrast adjustments within the ROI

These augmentations simulate clinical acquisition variability and contribute to a more robust model during training and evaluation.

3. Results

To evaluate the impact of preprocessing, we compared two models trained to classify the same set of non-contrast CT images into "Stroke" and "Non-Stroke" categories—one using raw images and the other using preprocessed data.
The CNN trained with standardized and augmented images showed superior performance across multiple metrics. It reached higher accuracy and AUC scores (0.98 vs. 0.93), with improved generalization during the validation phase.

These improvements were evident in:

- Loss and accuracy curves, showing better convergence.
- Confusion matrix, where the preprocessed model achieved a higher proportion of correct classifications
- ROC curves and prediction examples, which highlighted improved sensitivity and specificity

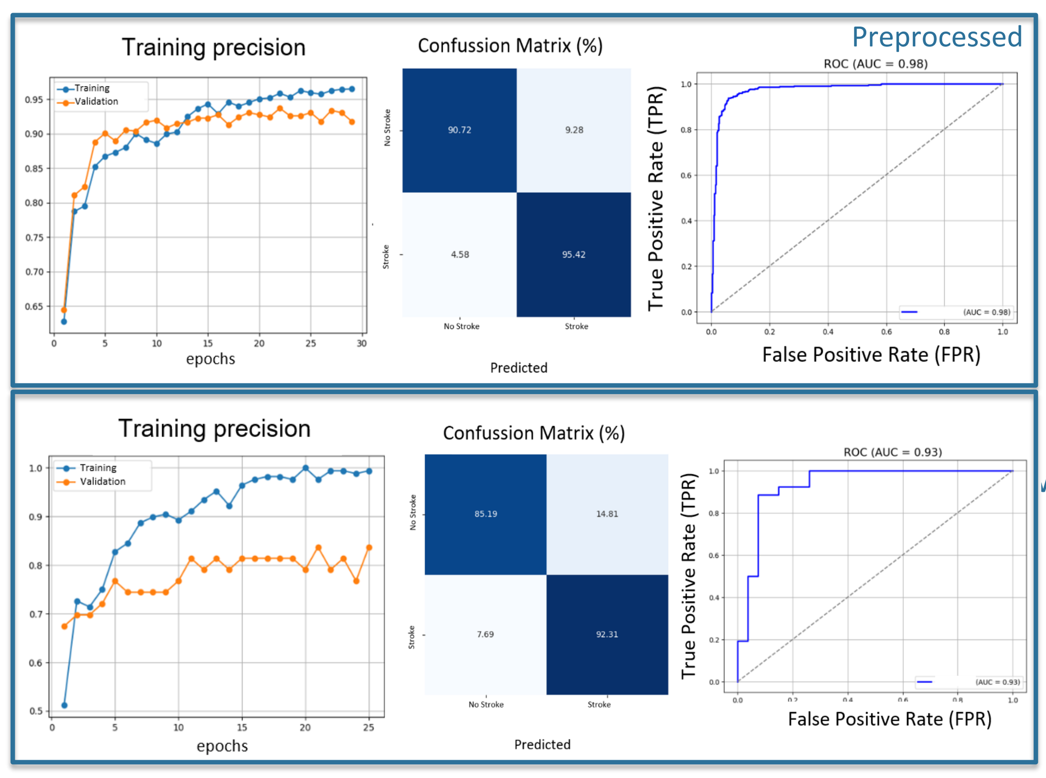

Figure 3. Metrics from preprocessed and raw models

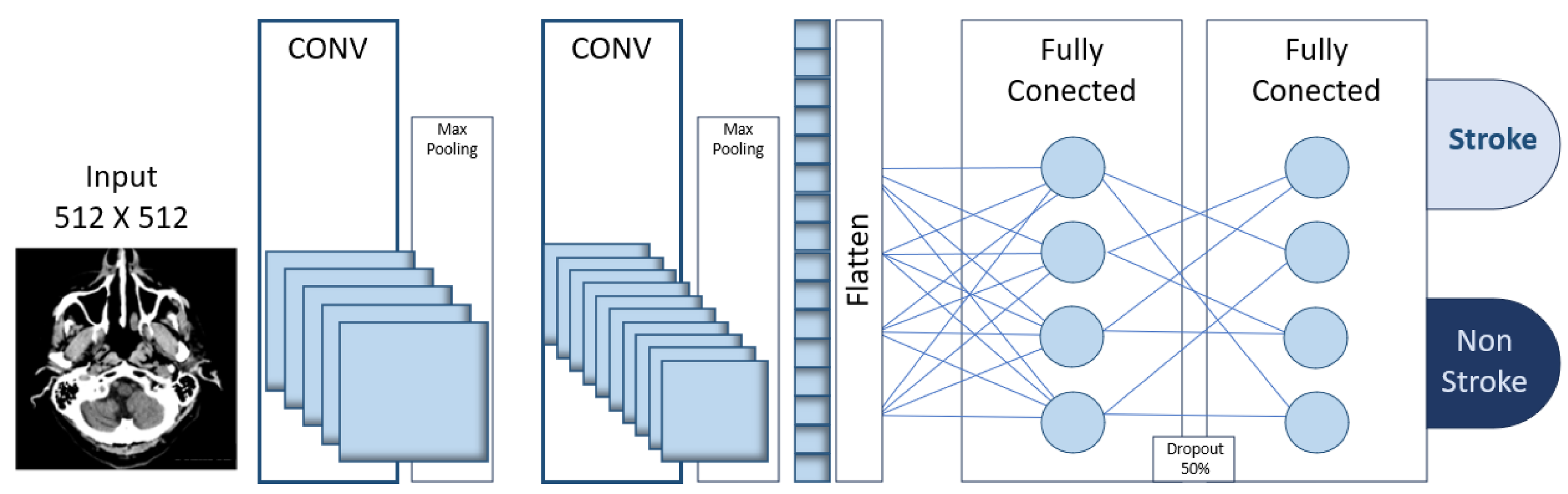

Figure 4. CNN Arquitechture

4. Conclusions

This study reinforces the importance of applying standardized preprocessing techniques when training convolutional neural networks (CNNs) for medical image classification. Following widely used practices—such as grayscale conversion, anatomical region cropping based on voxel content, and proportional resizing—allowed us to reduce model complexity while preserving clinically relevant structures.
The use of preprocessed data improved generalization performance, as reflected by a higher AUC score (0.98 vs. 0.93), and enhanced model robustness across training and validation. Additionally, common augmentation methods like rotations, vertical flipping, and contrast normalization contributed to simulating clinical variability.
Rather than proposing a novel approach, this work demonstrates the effective application of established preprocessing strategies tailored to non-contrast CT imaging. These results support the need to follow standard pipelines to ensure reproducibility, interpretability, and clinical relevance in deep learning applications for healthcare.

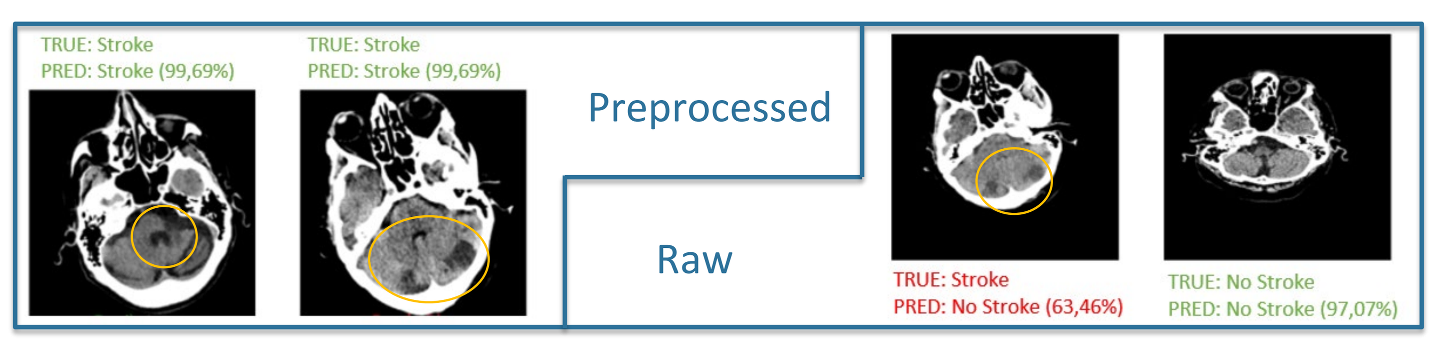

Figure 5. Predictions from processed and raw data

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