Intravenous Contrast Detection and Brain Filter Classification in Head CT Scans using a 3D CNN Model

Camila Aquemi Silva[1]; Tayran Milá Mendes Olegário[1]; Bruna Garbes Gonçaves Pinto[1]; Rafael Maffei Loureiro[1]; Artur José Marques Paulo[1]; Regiane Maria Ribeiro de Carvalho[1]; Márcio Rodrigues da Cunha Reis[1,2]; Leticia Rittner[1,3]; Joselisa Péres Queiroz Paiva[1]

[1]Hospital Israelita Albert Einstein, Sao Paulo, SP, Brazil, [2]Studies and Researches in Science and Technology Group (GCITE), Federal Institute of Goias - Goias, Brazil, [3]School of Electrical and Computer Engineering, University of Campinas (UNICAMP), Sao Paulo, Brazil.

Introduction

In neuroimaging, ensuring data quality for studies and subsequent processing in an automated pipeline is a significant challenge. The performance of machine learning models heavily relies on the quality of input data. With neuroimaging studies involving increasingly large datasets, visual inspection for quality control becomes impractical [1]. The following items describes the context for this study:

- DICOM serves as the standardized format for medical imaging;
- The Series Description attribute, as obtained through the DICOM tag (0008,103E), is a free-text field;
- The lack of information for precise CT series identification (Fig. 1) leads to labor-intensive visual inspection.

	Series Description (tag 0008,103E)
	Volume Partes Moles / Sem Contraste
A	NaN
B	Volume Osso / Sem Constraste
	Topo LAT 0.6 T80f
C	Topo AP 0.6 T80f
	Com / Contraste Volume
D	Volume
	Volume Partes Moles / Sem contraste
	Volume / Sem constraste

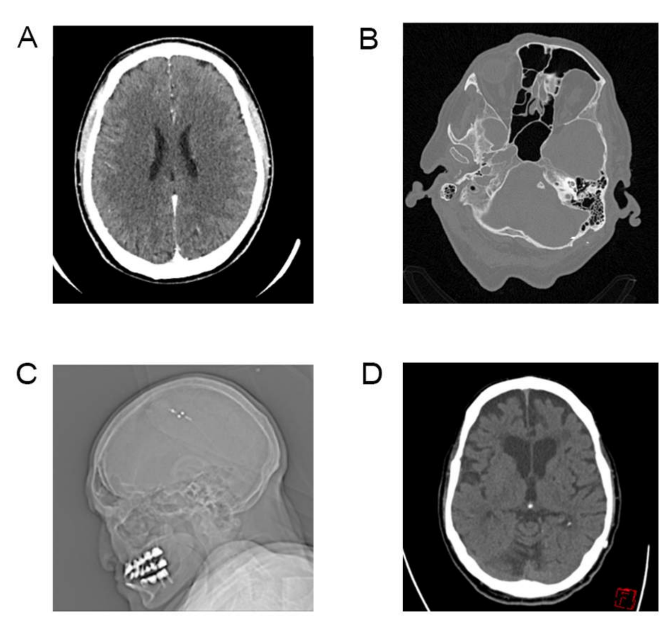

Figure 1. Example of DICOM standard metadata (Series Description tag) and a slice of the corresponding image for each series. Note that the description may contain terms such as "NaN" and other variations of non-standard or reliable terms.

Main goal

The present study focuses on the development of a three-dimensional convolutional neural network (3D CNN) model for discerning non-contrast CT series utilizing a brain filter from series containing contrast, bone filter, or other examination types like Cisternography and Angiography.

Methods

We used a dataset of head and neck computed tomography (CT) scans, sourced from the Picture Archiving and Communication System (PACS) at the Albert Einstein Israelite Hospital, comprising:

- A total of 554 anonymized axial volumetric CT series;
- We manually annotated for the presence of contrast and the type of filter used;
- It may or may not include radiological findings;
- Exclusion criteria: Non-volumetric series, i.e., containing fewer than 150 slices or Metadata pixel spacing (Tag 0028, 0030) greater than 1.3.

Images were resized to $128 \times 128 \times 64$ and voxel intensity of the whole dataset was adjusted to range from 0 to 100 Hounsfield Units (HU), since we are primarily interested in soft tissue structures, such as brain parenchyma.

TensorFlow was utilized for training the CNN, consisting of four modules of 3D convolutions, max-pooling layers, and normalization [2]. GRAD-Cam was employed on both CT Series with and without the head region, to assess whether the classification predictions were affected by extraneous information from the background of the CT scans (Fig. 2).

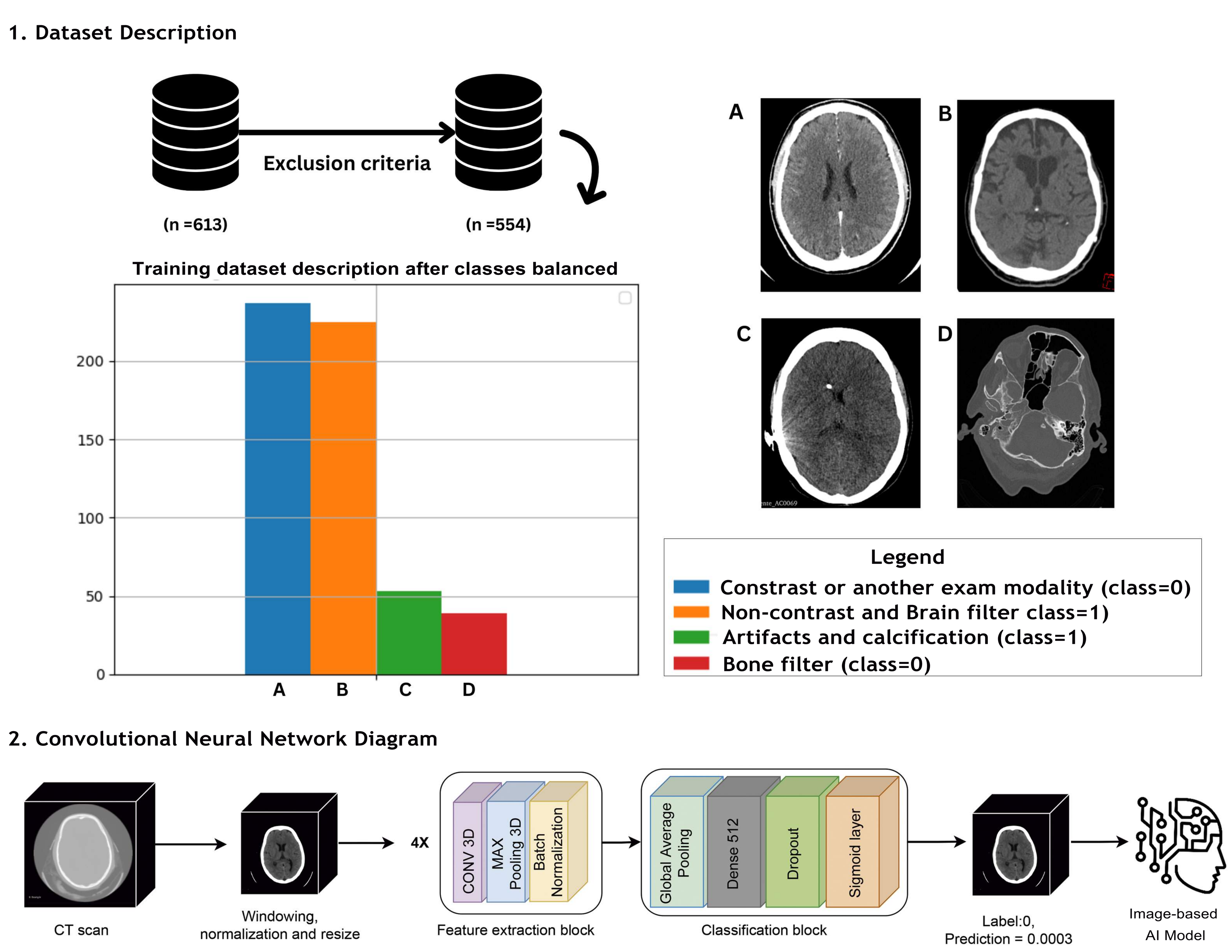

Figure 2. Item 1 depicts the dataset composition: series containing artifacts and calcification or non-contrast and brain filter labeled as 1; and all other variations presented on the dataset labeled as 0. Item 2 encompasses the image preprocessing steps and the Convolutional Neural Network diagram.

Results

- We report 99.5% area under curve (AUC) on the test set in individuals aged 65 or older (n = 178).
- We also tested the model on a publicly available datasetof anonymized head CT scans from the Indian population (n = 231). This sample represented a diversity of radiological findings across a wide age range. As we can see in Fig. 3, this test revealed an AUC of 94.63% in distinguishing between brain and bone filters in non-contrast head CT scans, indicating a promising ability of the model to generalize to different population groups.

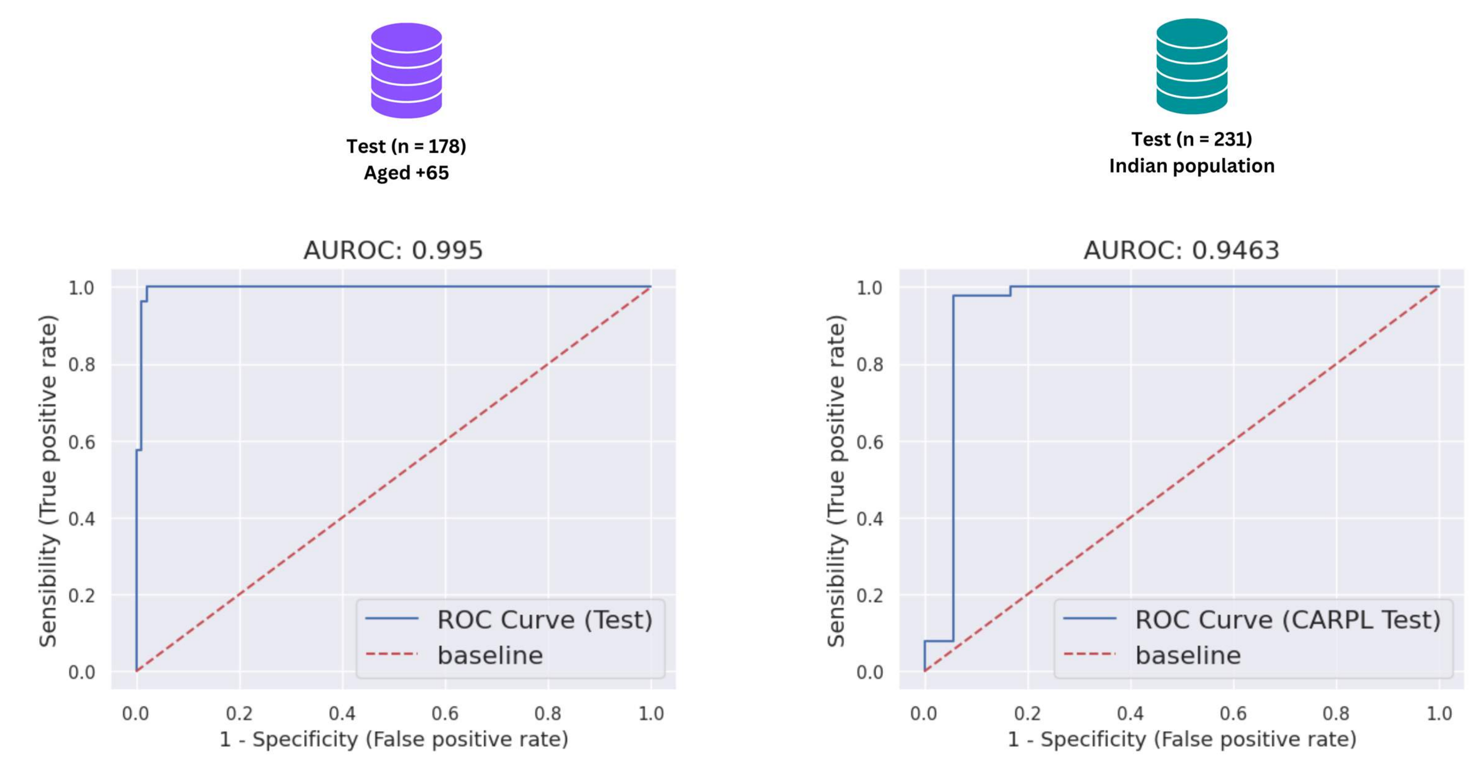

Figure 3. Results from the test datasets: 99.5% AUC on the in-house test set (left); and 94.63% on a public dataset (right)

Grad-CAM anaysis:

- We used the test dataset of individuals aged 65 years or older and extracted the head region from each volume.
- We can observe that the model's performance significantly drops to 53.9%, resembling that of a random classifier (Fig. 4), discarding the hypothesis that it might be learning from the background's noise.

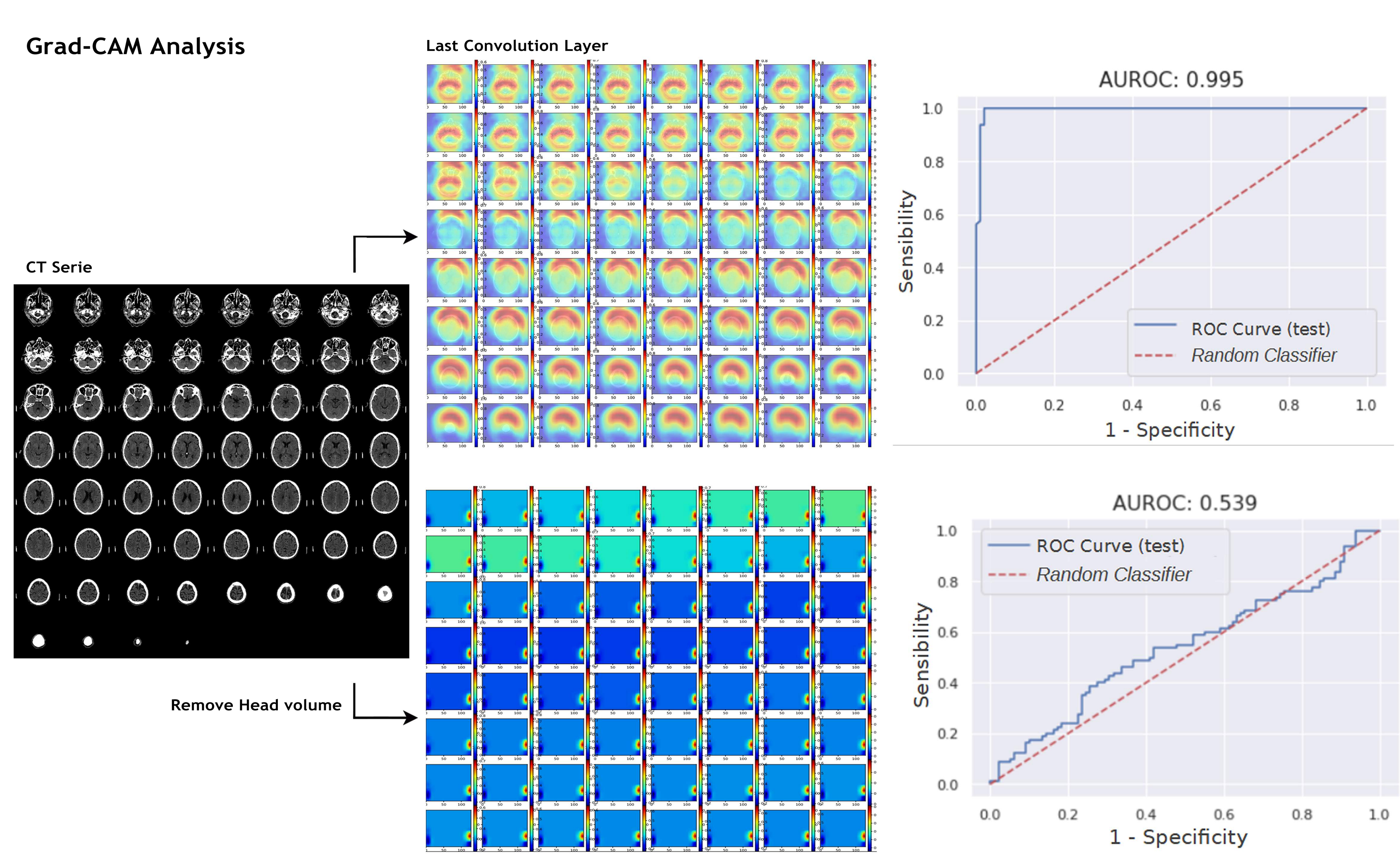

Figure 4. Grad-CAM obtained from the CT images and the corresponding ROC curve plots on the right.

Conclusion

- Machine learning was deemed necessary because the metadata-based approach for series identification proved insufficient and unreliable.
- Training a CNN to identify acquisitions at the voxel level within the CT series is a more robust solution.
- We aim to integrate this model in a pipeline that routes the relevant CT series to another image-based AI models.

References

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