DETECTION OF INTRACRANIAL HEMORRHAGES USING THE FOURIER TRANSFORM OF SINOGRAMS

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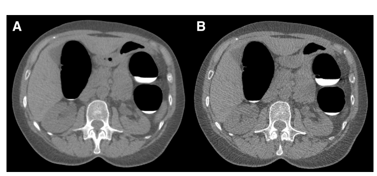
1 Abstract

Deep learning has significantly improved medical diagnostics with its ability to learn the underlying complex patterns.

A sinogram contains a sequence of X-ray projections of the patient into a lower dimensional space from different viewing angles, and a CT image is obtained as a result of applying reconstruction algorithms on the sinograms. In emergency cases of brain injury, time is critical for saving lives, especially considering the considerable time taken for CT reconstruction. To address this challenge, we propose a novel approach: detecting brain trauma directly from the sinogram. Our method explores the Fourier transform of sinograms, leveraging its efficiency and suitability for implementation on GPUs. Preliminary results are promising, indicating the potential for further research in this area.

2 Introduction

The Computed Tomography (CT) scan is an important medical imaging modality with a wide range of applications. Its importance



lies in its ability to provide detailed cross- sectional images of the body.The generation of a CT scan involves two main stages: the sinogram acquisition phase and the CT reconstruction phase.In the acquisition phase, X-ray projections of a specific anatomical slice are obtained from multiple angles as the X-ray source and detector rotate around the patient. Each projection represents a line of data, and these lines of data are arranged in the sinogram, with one axis representing the angle of the X-ray source or detector and the other axis representing the number of detectors or data channels.

The CT reconstruction phase involves various algorithms to transform the sinogram into a cross-sectional CT image of the scanned anatomy. These algorithms use the information from the sinogram to determine the X-ray attenuation values at different points within the slice.
The effective utilization of the sinograms can provide a more comprehensive and precise representation of the patient's anatomy compared to relying solely on CT images. Exploring ways to exploit and leverage the information in the sinograms can potentially enhance diagnostic performance, benefiting patient care and medical decision-making. In this regard, our exploration delved into Fourier domain-based analysis of sinograms.

3 Dataset

This study is performed on the publicly available RSNA dataset containing brain CT scans with hemorrhages. The details of the dataset considered for the current study are tabulated below.

Table 1: Dataset Split for Training, Validation, and Testing.

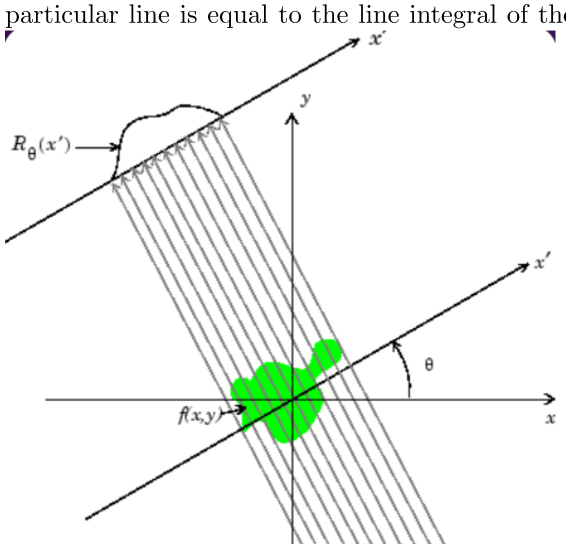
Dataset	Subjects	Slices
Train	1000	42,724
Validation	200	8,421
Test	250	10,596
Total	**1450**	**61,741**

The sinogram consists of slices, each with dimensions (360, 362). Here, 360 denotes the various angles from which the projection is captured, and for each angle, the length of the projection is 362.

4 Theory

- RADON TRANSFORM

  It is the integral transform that takes a function f defined on the plane to a function Rf defined on the space of lines in the plane, whose value at a particular line is equal to the line integral of the function over that line.



$$R(r,\theta) = \int_{-\infty}^{\infty}\int_{-\infty}^{\infty} f(x,y)\,\delta(x\cos\theta + y\sin\theta - r)\,dx\,dy$$

4.1 Fourier Slice Theorem

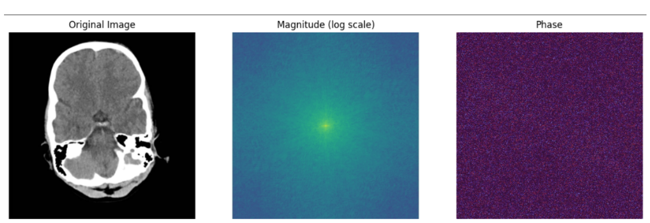
The Fourier-slice theorem or the central slice theorem relates the 1D Fourier transform of a projection. By the central slice theorem, the Fourier transform of Rf in direction

$$\hat{n}$$

is equivalent to the slice of the Fourier transform of f along

$$\hat{n}$$

$$\begin{aligned}\mathbb{F}_1[Rf](k,\hat{\boldsymbol{n}},z) :&= \int_{-\infty}^{\infty} \exp\left(-2\pi ikt\right) Rf(t,\hat{\boldsymbol{n}},z)\,\mathrm{d}t \\ &= [\mathbb{F}_2 f]\,(k\hat{\boldsymbol{n}},z),\end{aligned}$$



Typically, in the reconstruction process, we first transform the projection data using Fourier analysis, then apply a filter to enhance its quality, and finally back-project the refined data to reconstruct the image.

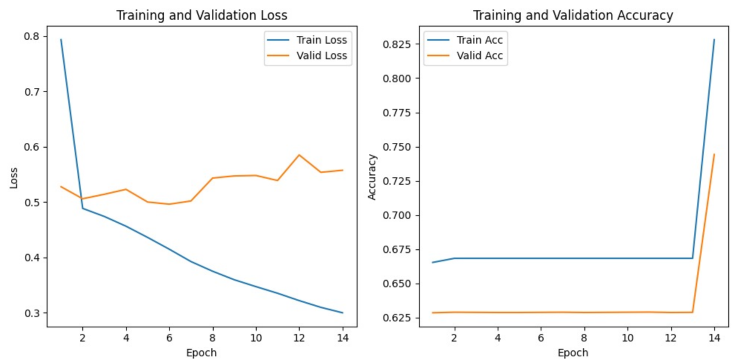
5 Method and Implementation

We crafted a data loader for the dataset, where each image measures 360 by 362 pixels, comprising three channels. These channels represent distinct intensities of scans conducted on different regions of the brain. This approach accommodates the varying radiation intensities needed for optimal imaging of specific brain areas.
We utilized the Fast Fourier Transform (FFT) operation on each angle and for each channel of the dataset. Then, we computed the magnitude of the Fourier coefficients. With these processed samples, the data is now prepared to be fed into the neural network

Initially, we employed a basic neural network architecture consisting of three convolutional layers and two fully connected layers. The training dataset comprised 75,000 samples, while the validation dataset contained 25,000 samples, with a batch size of 50. We trained the model for 15 epochs. Initially, we observed promising results on the training set, but eventually, the model became overfit. However, despite the overfitting, the test accuracy remained at a respectable 71 percent.

In response to the overfitting issue, we opted for a lighter version of the model. This involved using smaller filter sizes, reducing the number of fully connected layers to one, and incorporating dropout layers into the architecture.

Subsequently, we executed this model and observed a reduction in overfitting, accompanied by an increase in test accuracy to 74 percent. The training and validation plots are depicted below.



6 Conclusions and Future Research Prospects

The results achieved, while not groundbreaking, are nonetheless promising and encouraging.
They indicate that Fourier analysis of sinograms holds potential for detecting brain injuries, offering the prospect of significantly reducing CT scan reconstruction time and expediting patient diagnosis, ultimately saving lives.

We suggest a few avenues for further research.

- We have so far focused solely on the magnitude of the Fourier coefficients. Exploring the phase of the coefficients, or even combining both magnitude and phase for prediction, presents intriguing possibilities.

- In our preliminary work, we employed a simple convolutional neural network (CNN). However, considering the interdependence of slices, exploring the use of recurrent neural networks (RNNs) could yield valuable insights.

- Combining results from Fourier analysis with conventional approaches warrants investigation to ascertain whether enhanced performance and outcomes can be achieved.

In conclusion, this area holds significant promise for further research and stands to offer substantial benefits to the field of medical imaging.