



G03

A SELF SUPERVISED ANOMALY DETECTION APPROACH IN CT SCANS USING CONVOLUTIONAL AUTOENCODER

• Mouad KHAZNAOUI, Hiba CHARKANI-ELHASSANI, Sourou Alfred SODJI, Achraf JEMALI, MID@S, Ecole Centrale Casablanca, Morocco
• Oumayma Banouar, FSTG, UCAM, Marrakesh | Oumayma Ouedrhiri, UQTR, Canada

Contact : mouad.khaznaoui@centrale-casablanca.ma ; Tel : 06 14 30 54 56

1- INTRODUCTION & MOTIVATION

In the rapidly advancing world of medical imaging, our initiative utilizes autoencoders to make a significant leap in CT scan diagnostics by prioritizing the automation of anomaly detection. This focus aims to radically transform the diagnostic decision-making process, addressing the critical need for heightened accuracy in an era overwhelmed by the increasing volume of medical images and the potential for human oversight. By arming radiologists with sophisticated, automated tools for precise anomaly detection, our project is not just enhancing diagnostic accuracy; it is redefining the speed and reliability of the diagnostic process itself. This innovative approach promises to facilitate earlier interventions, thereby significantly improving patient care and the overall efficiency of healthcare services. Our commitment to this technology underscores our vision to pioneer advancements in automated diagnostics, ultimately enabling healthcare professionals to make faster, more informed decisions that lead to better patient outcomes.

2- ANALYSIS & DESCRIPTION OF THE GROUP WORK

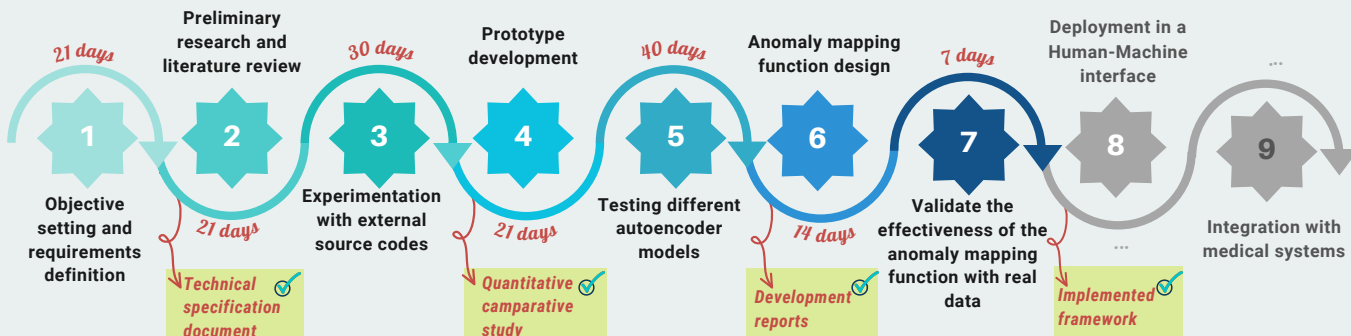
PROBLEMATIC

How can we improve medical diagnosis through technology by increasing its precision while optimizing available medical resources?

GOAL

Develop an automated system for detecting anomalies in CT-scan images, improving medical diagnosis and management of health resources.

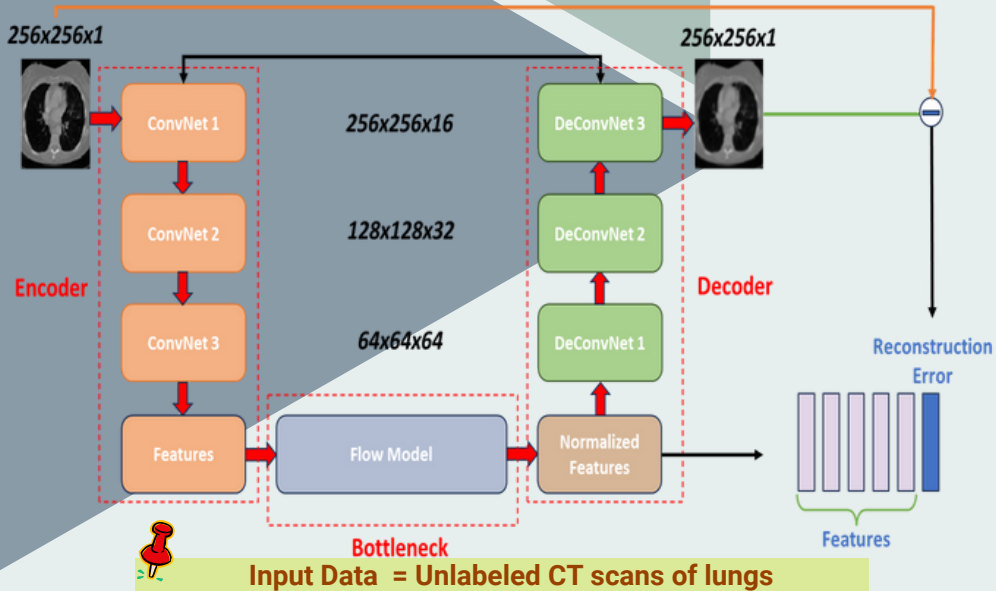
PROJECT PIPELINE



3- OVERVIEW OF THE PROPOSED FRAMEWORK

A- FEATURE EXTRACTION

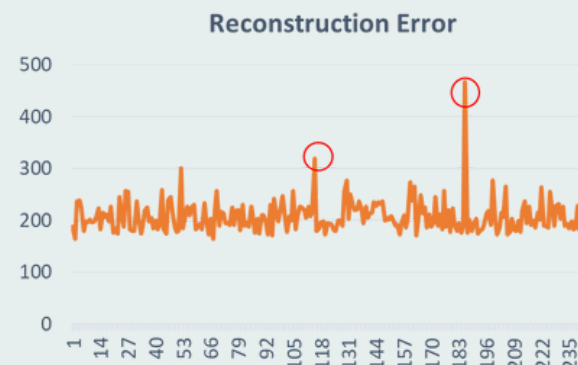
The Encoding and Decoding Processes of the Autoencoder using **ConvNets** and **DeConvNets**, Respectively. The Encoding and Decoding Processing are Symmetric and have the Same Layers in each Section.



Input Data = Unlabeled CT scans of lungs

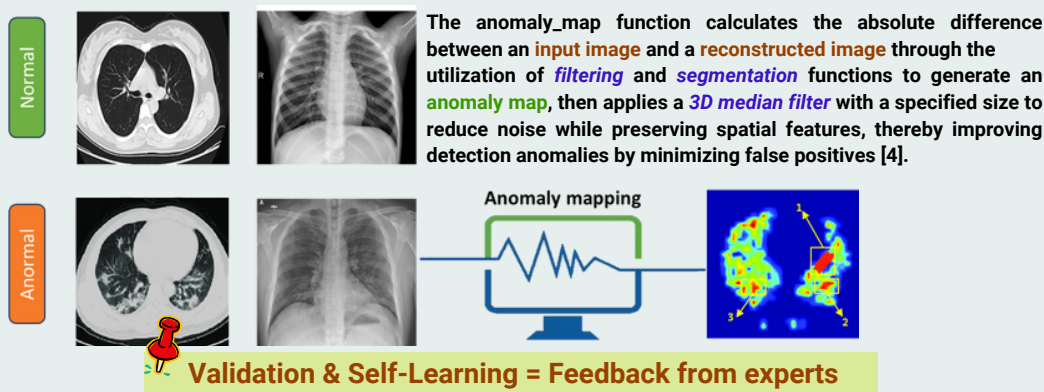
B- ANOMALY CLASSIFICATION

The MAE score of abnormal data tends to be higher than the normal data threshold. The distribution of the MAE scores determines the threshold; 92% of the data was between 150 and 300. Therefore, by looking at this distribution, the basic threshold for anomaly detection was set at 300.



C- ANOMALY MAPPING

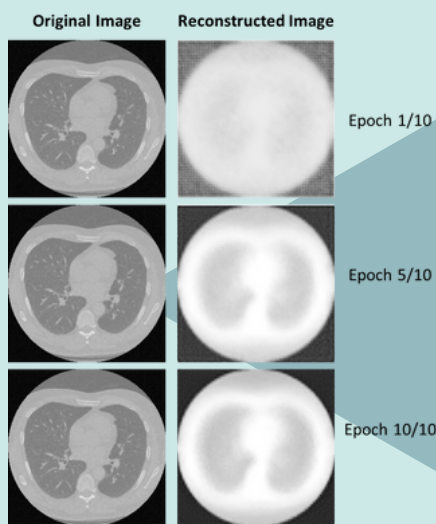
Following classification, the next step involves pinpointing anomalies detected by the abnormal scanner.



D- RESULTS AND DISCUSSION

CT images of lung cancer are used as a dataset (1). A total of 297 images are marked separately for training and testing purposes. Convolutional autoencoders are implemented by adopting high-level neural network application package – using libraries such as matplotlib 3.5, sklearn 1.0, torch 1.11, imageio 2.9, and tensorflow 2.8. The code is written in python 3.11 and executed on Google Colab Pro with GPU acceleration.

Image Reconstruction



Classification task

Given the data imbalance, direct training could lead to erroneous results while still yielding high accuracy scores. We need to balance the data and ensure good accuracy for both classes.

	Accuracy
CNN-based architecture [1]	77%
Firefly algorithm with SVM [2]	78%
Adversarial autoencoder-based [3]	62%
Our implemented approach	82%

1 <https://www.kaggle.com/datasets/kmader/finding-lungs-in-ct-data>
2 <https://luna16.grand-challenge.org/Data/>
3 <https://www.spyder-ide.org/>
4 <https://keras.io/>
5 <https://www.tensorflow.org/>
6 <https://www.python.org/>

4- CONCLUSION & PERSPECTIVES

Goals

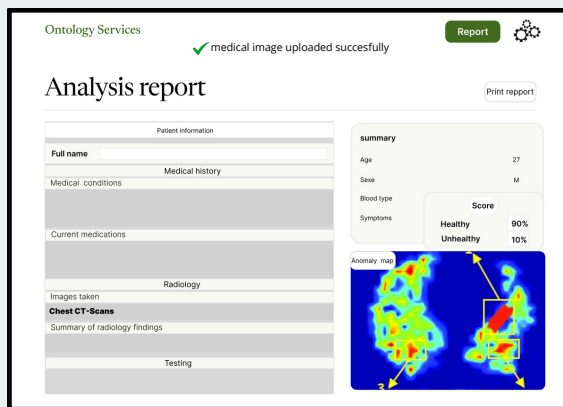
- Increased detection accuracy of anomalies.
- An unsupervised learning framework without the need for lesion marking
- Automated lesion segmentation

Added value

- A friendly user interface
- Automatic report generation
- Improved automatic lesion segmentation
- Generation of an annotated database thanks to feedback from the doctor

Perspectives

- Continuous model performance improvement
- Implementing the model on other types of images (MRI, X-ray)
- Adapting the model to CT scans of different parts of the body



The **user interface** has been designed to be user-friendly for healthcare professionals. The application provides to the doctor clear and relevant information about the status of their CT-scan, making it easy to understand the results. They can perform a number of actions: print reports, save medical reports or give their opinion. The doctor can personalize the display of his application to provide more information when analyzing the results.

BIBLIOGRAPHY

- [1] Sharma, S., Kaur, M., & Saini, D. (2019). Lung cancer detection using convolutional neural network. *International Journal of Engineering and Advanced Technology*, 8(6), 3256–3262. <https://doi.org/10.35940/ijeat.F8836.088619>.
[2] Lung Anomaly Detection System (LADS) Using SVM based on Firefly Algorithm. (2017). *International Journal of Science and Research (IJSR)*, 6(7), 540–544. <https://doi.org/10.21275/art20175294>
[3] Beggel, L., Pfeiffer, M., & Bischl, B. (2020). Robust Anomaly Detection in Images Using Adversarial Autoencoders. In *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)* (Vol. 11906 LNAI, pp. 206–222). Springer. https://doi.org/10.1007/978-3-030-46150-8_13
[4] Guoting Luo, Wei Xie, Ronghui Gao, Tao Zheng, Lei Chen, Huaiqiang Sun. 5 August 2022. Unsupervised anomaly detection in brain MRI: Learning abstract distribution from massive healthy brains. 25 January 2023. <https://doi.org/10.1016/j.combiomed.2023.106610>