HEARTLENS:
SELF-SUPERVISED LEARNING AND FOUNDATIONAL MODELS IN MEDICAL IMAGING

Center for Applied Artificial Intelligence
Pro Scientia et Humanitate

HEARTLENS

Multidisciplinary Team: Bridging Clinical and Technical Expertise

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CORONARY ARTERY DISEASE

CORONARY ARTERY CALCIUM (CAC)

Cardiovascular Disease (CVD):

- Leading cause of death globally, with **17.9 million fatalities in 2019** (32% of all deaths worldwide).

Coronary Artery Disease (CAD):

- A major type of CVD that affects the blood vessels supplying the heart muscle.
- Typically caused by atherosclerotic narrowing and blockage of coronary vessels.
- Responsible for 371,506 deaths in the U.S. in 2022.

Coronary Artery Calcium (CAC):

- CAC is a highly accurate marker of CAD.
- Used as a specific metric to assess the severity of CAD.

CORONARY ARTERY DISEASE

CORONARY ARTERY CALCIUM (CAC)

A chest CT scan is recommended to assess for the presence of CAD.

The primary goal of a cardiac CT scan for calcium scoring (CAC) is to evaluate the likelihood of CAD.

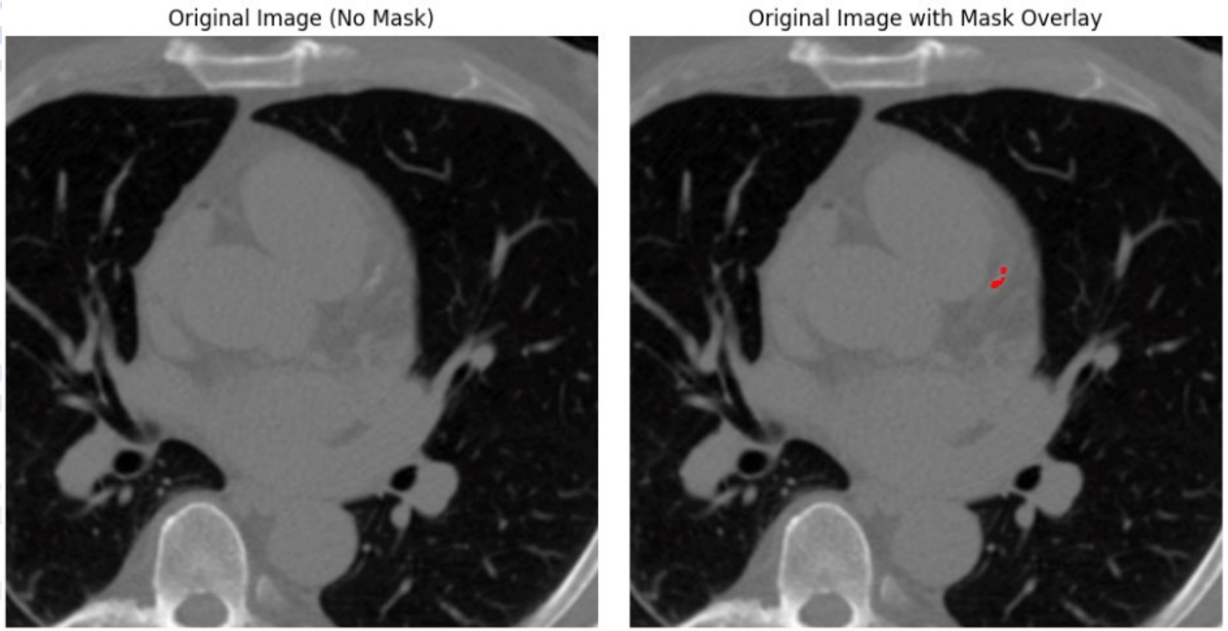


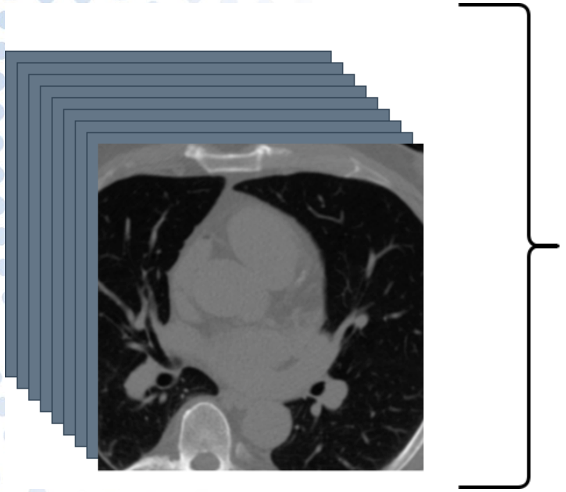
Fig. 1: A CT slice including calcified plaques and represented with its annotation.

CORONARY ARTERY DISEASE

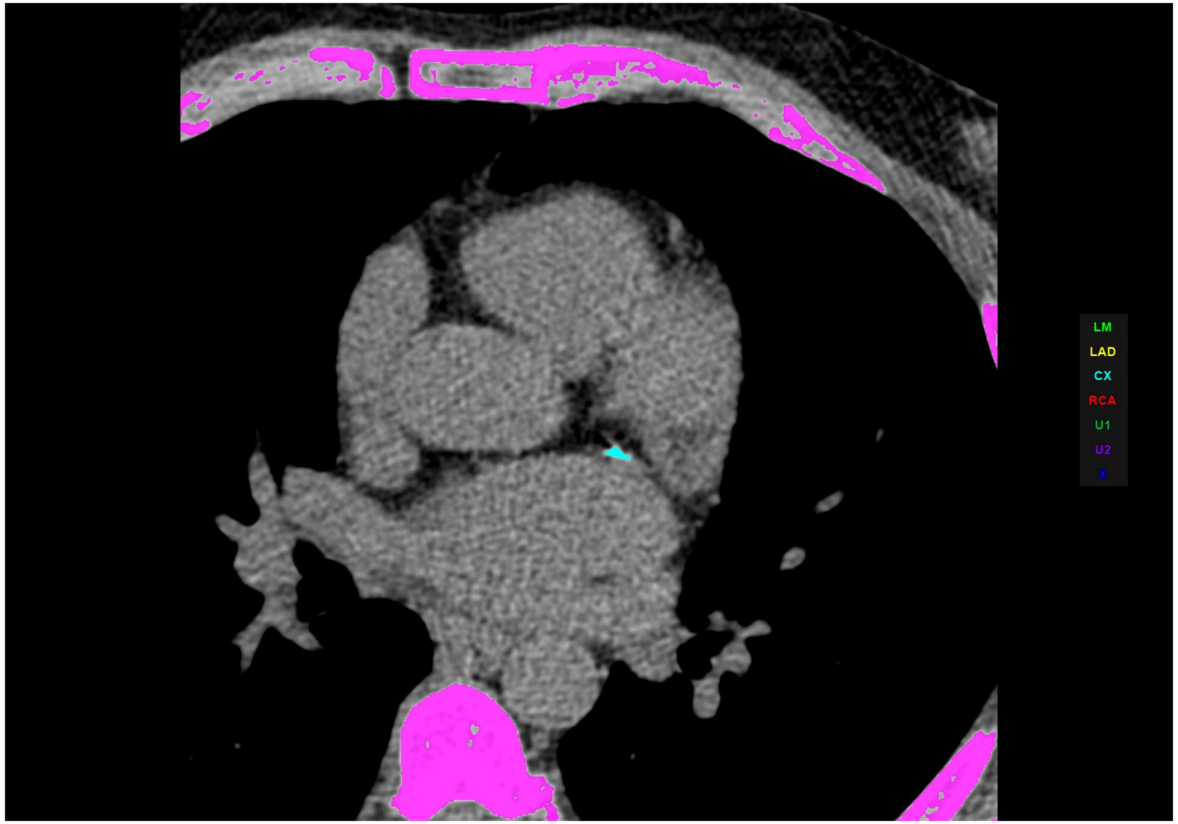
CORONARY ARTERY CALCIUM (CAC)

CAC scoring is a risk assessment method that sums up the amount of plaque detected in a CT scan.

A chest CT scan may consist of multiple slices, including those that show calcified areas.



Overview of 3D Chest CT Scan
Combines 2D image data with no maximum limitation on the number of slices.
Data range: [-1024. 3072] or [0,4096] (2^{12})



CORONARY ARTERY DISEASE

CORONARY ARTERY CALCIUM (CAC)

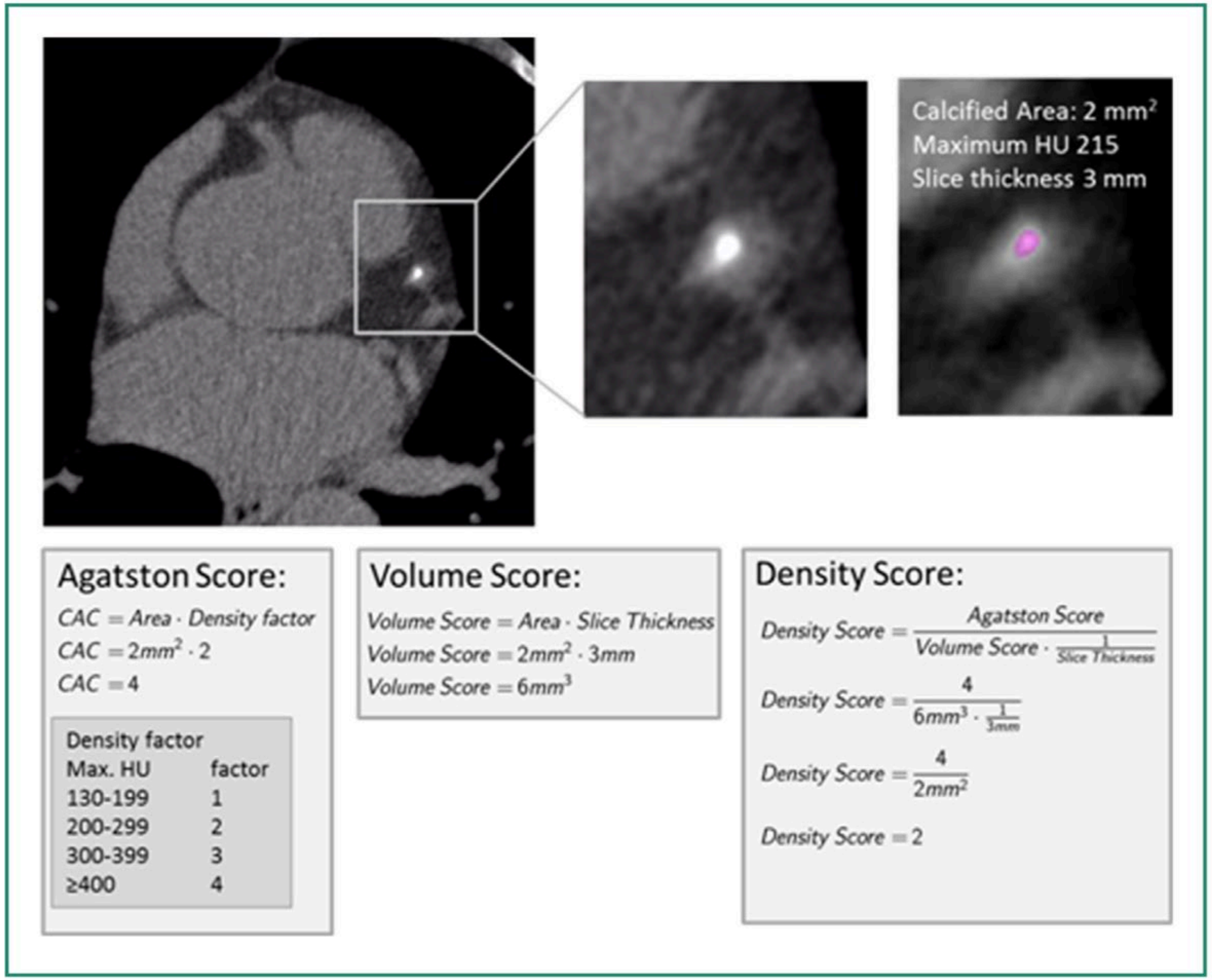
CAC Scoring Methods:

1) **Agatston Score**
2) Volume Score
3) Density Score

Each slice is evaluated using one of these scoring algorithms, and the sum of these scores constitutes the overall CAC score.

The most well known and used scoring method is **Agatston Score**.

Minimum threshold is 130 in HU units [1].



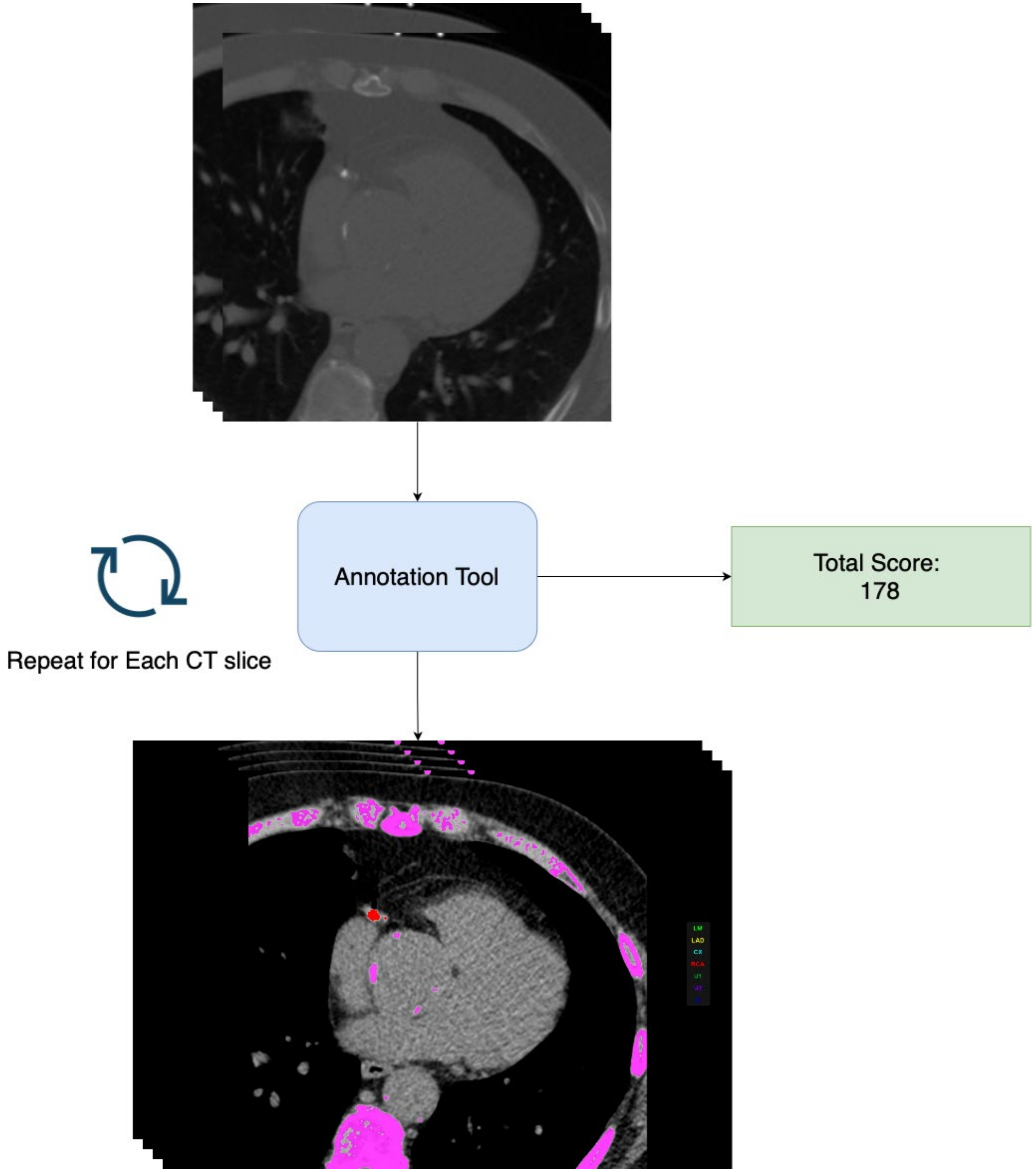
CORONARY ARTERY DISEASE

HOW RADIOLOGISTS EVALUATE CT SCANS ?

- Challenges:
- Bones and other dense structures need to be evaluated separately using an annotation tool and human intervention if their density exceeds 130 Hounsfield units (HU).

- A radiologist must determine which slices should be evaluated using an annotation tool.

- The annotations generated are not suitable for AI-driven approaches.



CORONARY ARTERY DISEASE

CORONARY ARTERY CALCIUM (CAC)

CAC score (Agatston method)	Risk analysis	Clinical correlation
0	Absent/ No risk	Low risk of future cardiovascular events.
1-10	Minimal	Minimal atherosclerosis may be present with a low risk of future cardiovascular events.
11-100	Mild	There is likely mild to minimum coronary artery stenosis. A mild risk of coronary artery disease exists.
101-400	Moderate	Reasonable amount of plaque can be confirmed. Has a moderately increased risk of future cardiovascular events.
>400	High	A high coronary calcium score corelated with a significant risk of having a cardiovascular event (such as myocardial ischemia) in near future.

Tab. 1: Overall Risk Assessment for CAC Scoring. [2]

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GOALS:

- Automating CAC Risk Assessment: Streamlining the process for accurate and efficient diagnosis.
- Early Detection: Identifying CAC at an earlier stage to enable timely intervention.
- Interpreting CT Scans with LLM Models: Utilizing advanced models to analyze and interpret CT scans when necessary.
- AI-Driven Label Generation: Eliminating human effort in annotation to produce labels suitable for AI training.

HOW ?

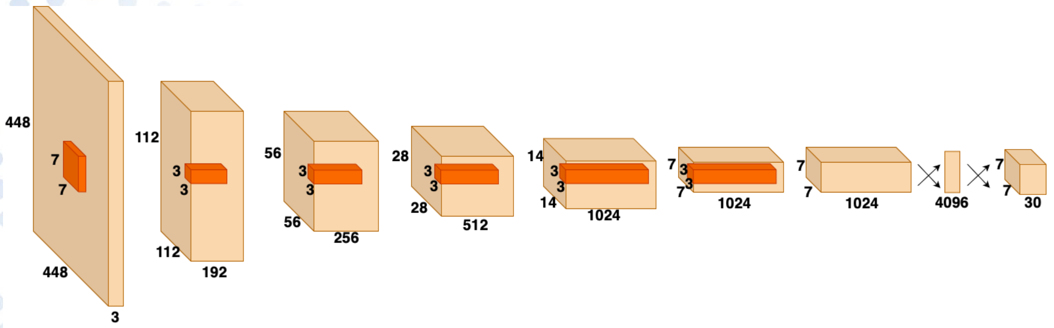
RELATED STUDIES

GENERAL OVERVIEW FOR RELATED STUDIES

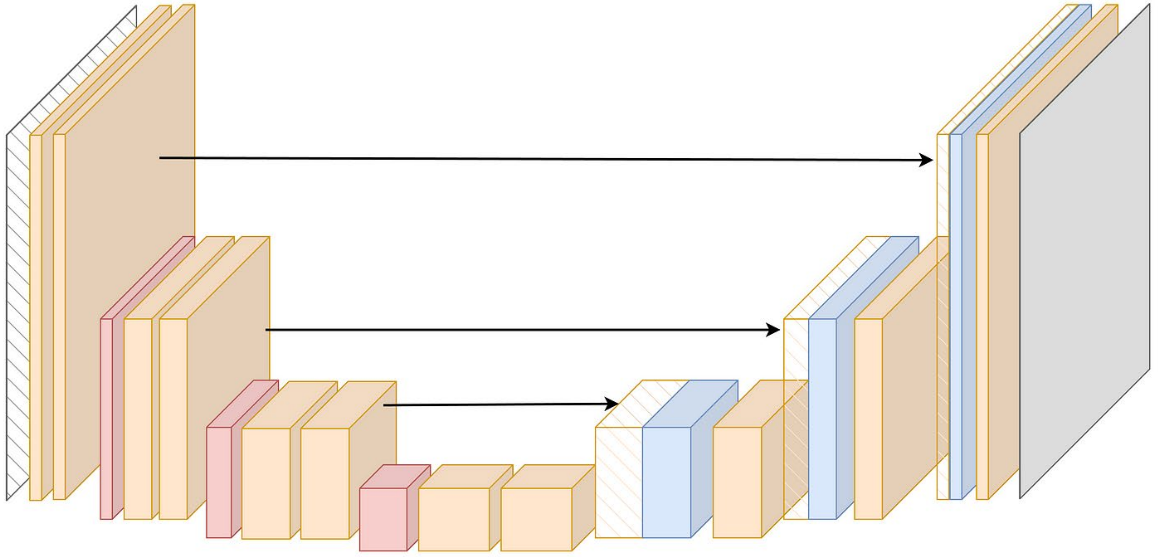
Completely **supervised** training techniques are used.

Mostly CNN and U-NET (CNN) architectures are employed for risk assessment.

Average accuracy in related studies generally higher than %90. [3]



Basic CNN classifier architecture

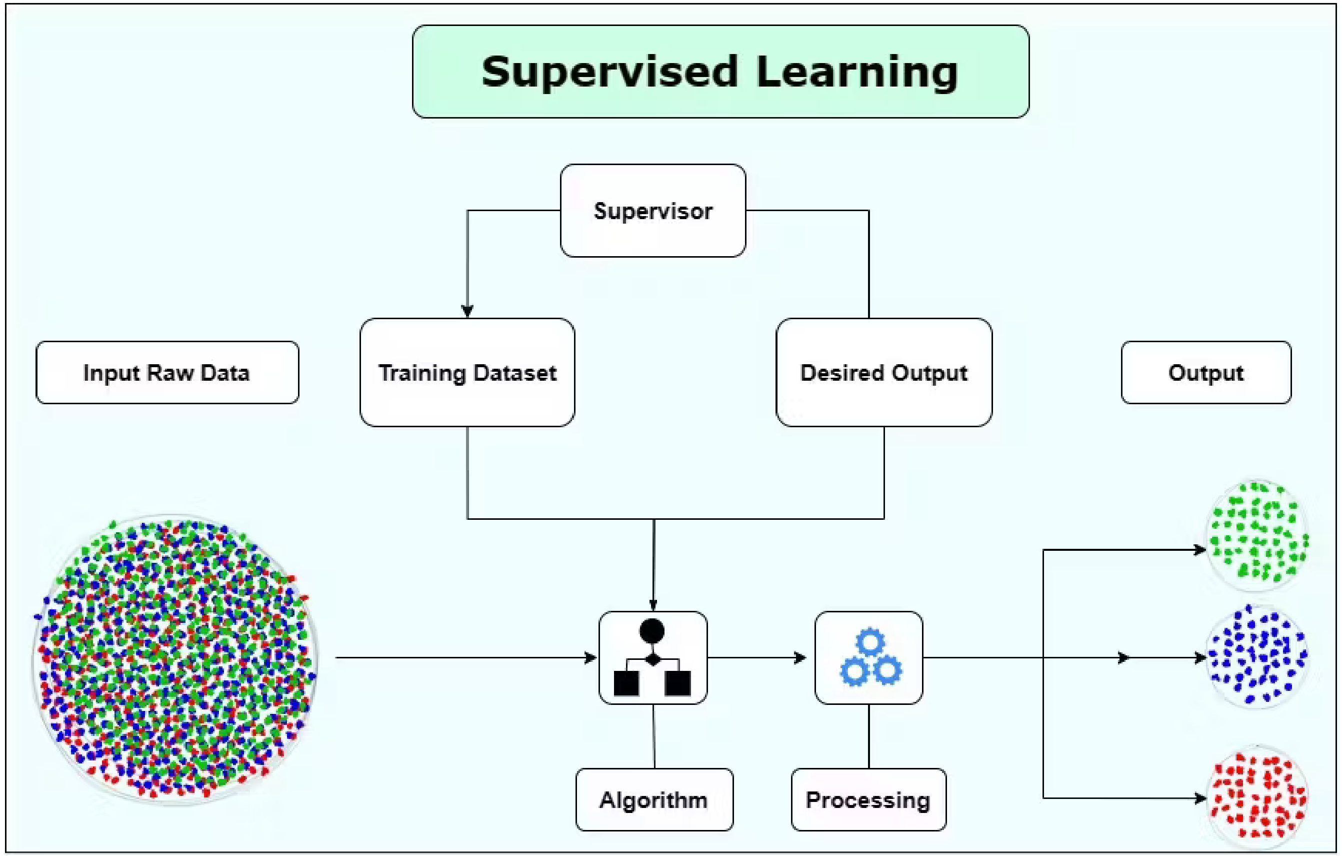


Basic U-NET architecture

RELATED STUDIES

SUPERVISED LEARNING

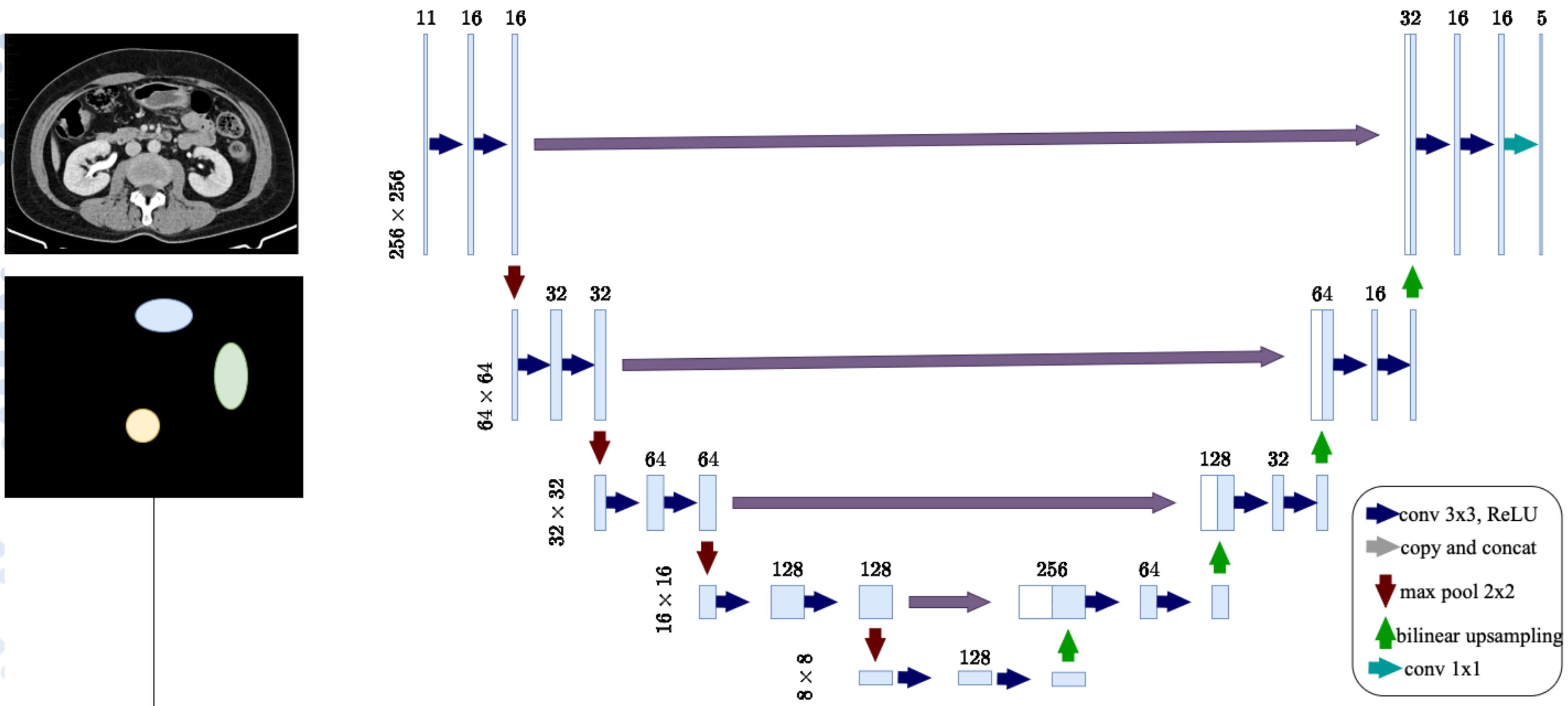
- Needs a balanced and high quality dataset.
- Tends to memorizing and overfitting the dataset trained recently.
- Lack of representations limits transferability and adaptability.

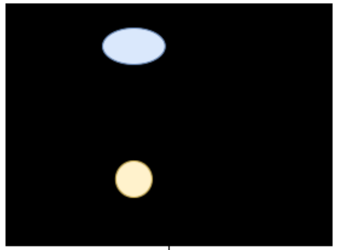


RELATED STUDIES

APPLICATIONS IN SUPERVISED LEARNING

Segmentation





$$p_i^{(k)} = \frac{\exp(z_i^{(k)})}{\sum_{j=1}^{K} \exp(z_i^{(j)})},$$

$$\mathcal{L}_{\text{multi-class}} = -\frac{1}{N}\sum_{i=1}^{N}\sum_{k=1}^{K} y_i^{(k)} \log(p_i^{(k)}),$$

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RELATED STUDIES
CHALLENGES

Challenges in Training:

- Imbalanced dataset.
- Trained models are not transferable.
- Inadequate publicly available data

Challenges in Datasets:

- The proportion of annotated data is than 10% in CT scans.
- The average calcified area size in publicly available datasets ranges from 5 to 10 pixels in a 512x512 annotated CT slice.
- The annotated area in a CT scan constitutes only **0.0001%** of the total pixel count.

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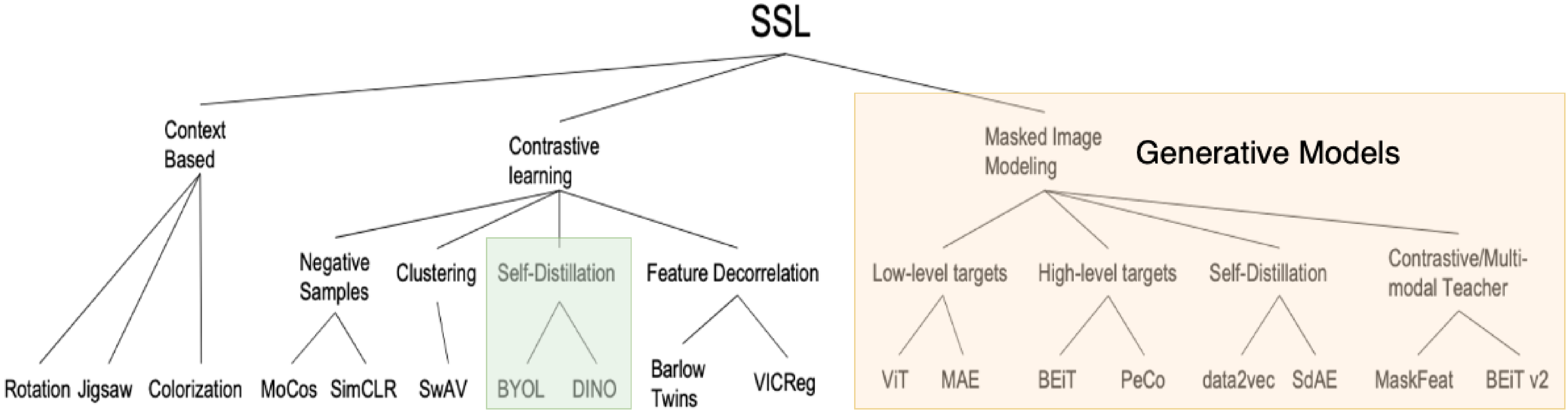
SELF-SUPERVISED LEARNING

TAXONOMY

Pretext-Tasks:

An artificially created task that a model is trained on using unlabeled data.



Several representative pretext tasks of SSL [3]

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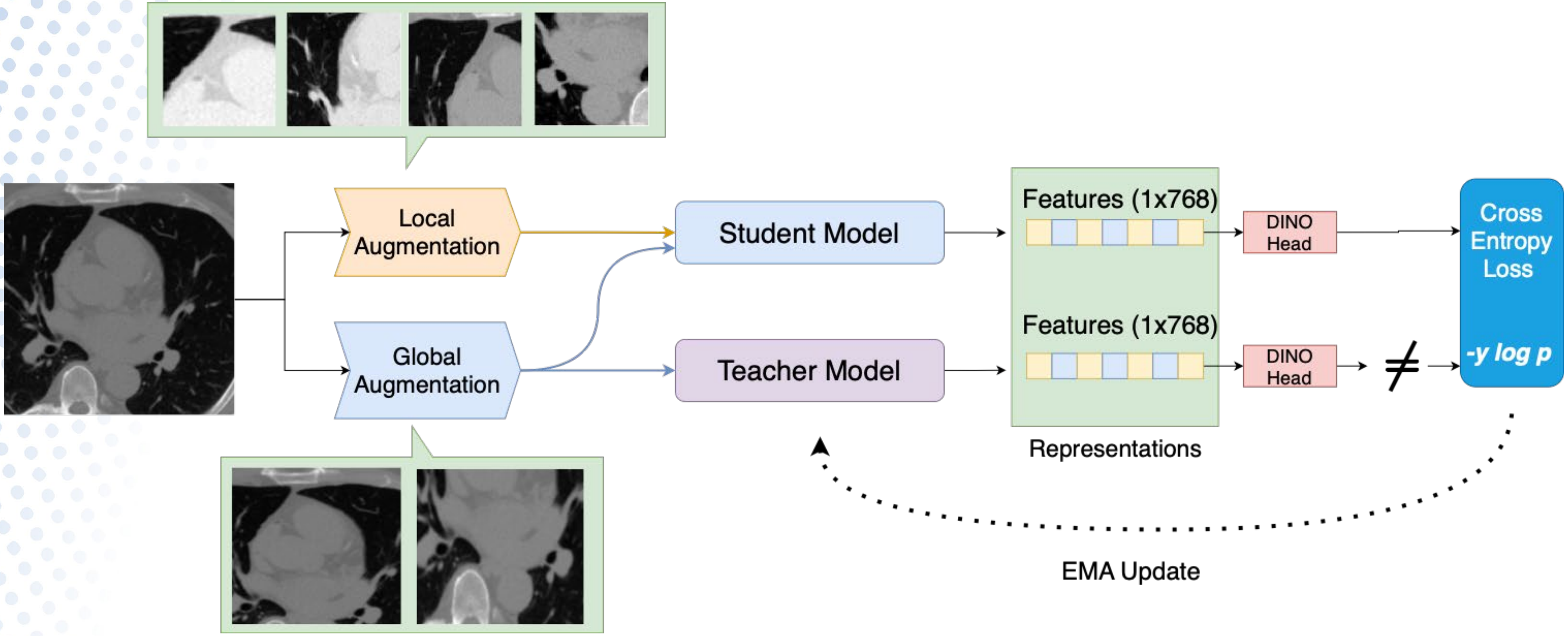
SELF-SUPERVISED LEARNING

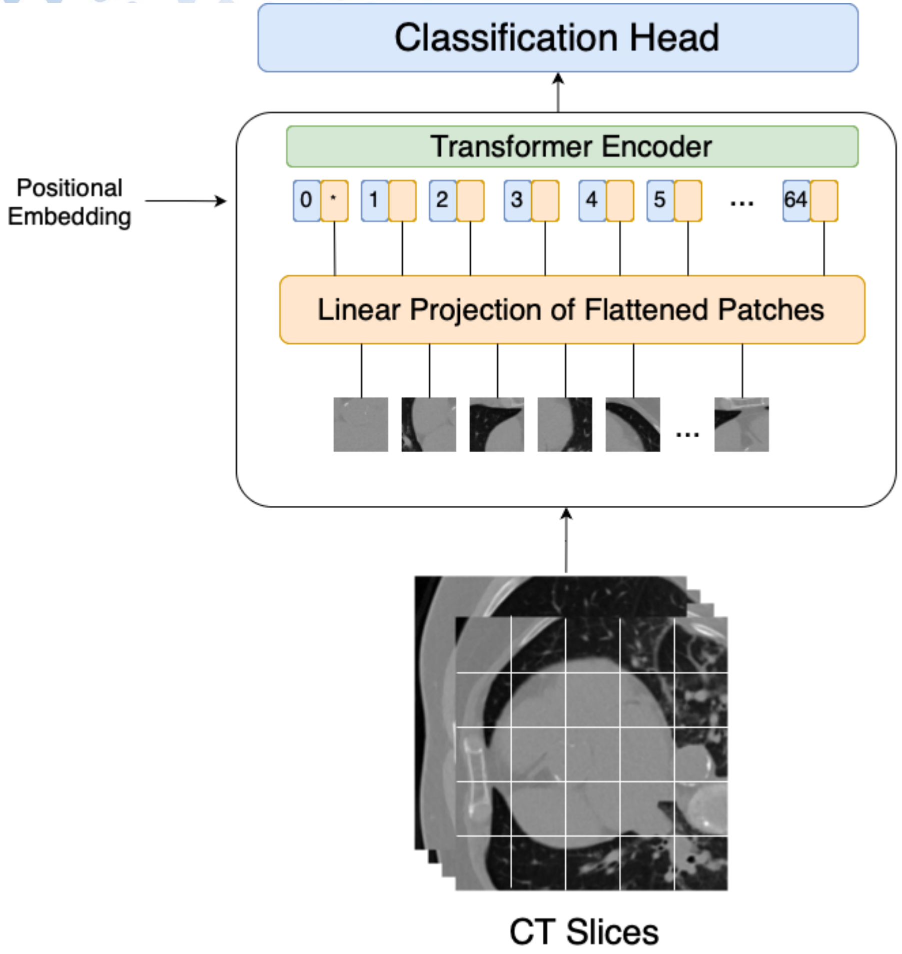
DINO-TRAINING TECHNIQUE

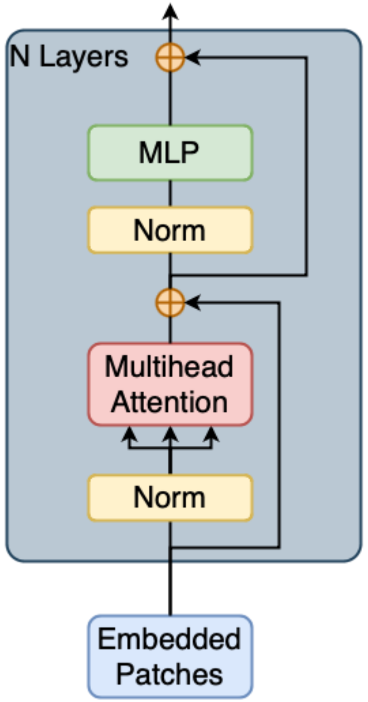
DINO



SELF-SUPERVISED LEARNING

VISION TRANSFORMERS (VIT)





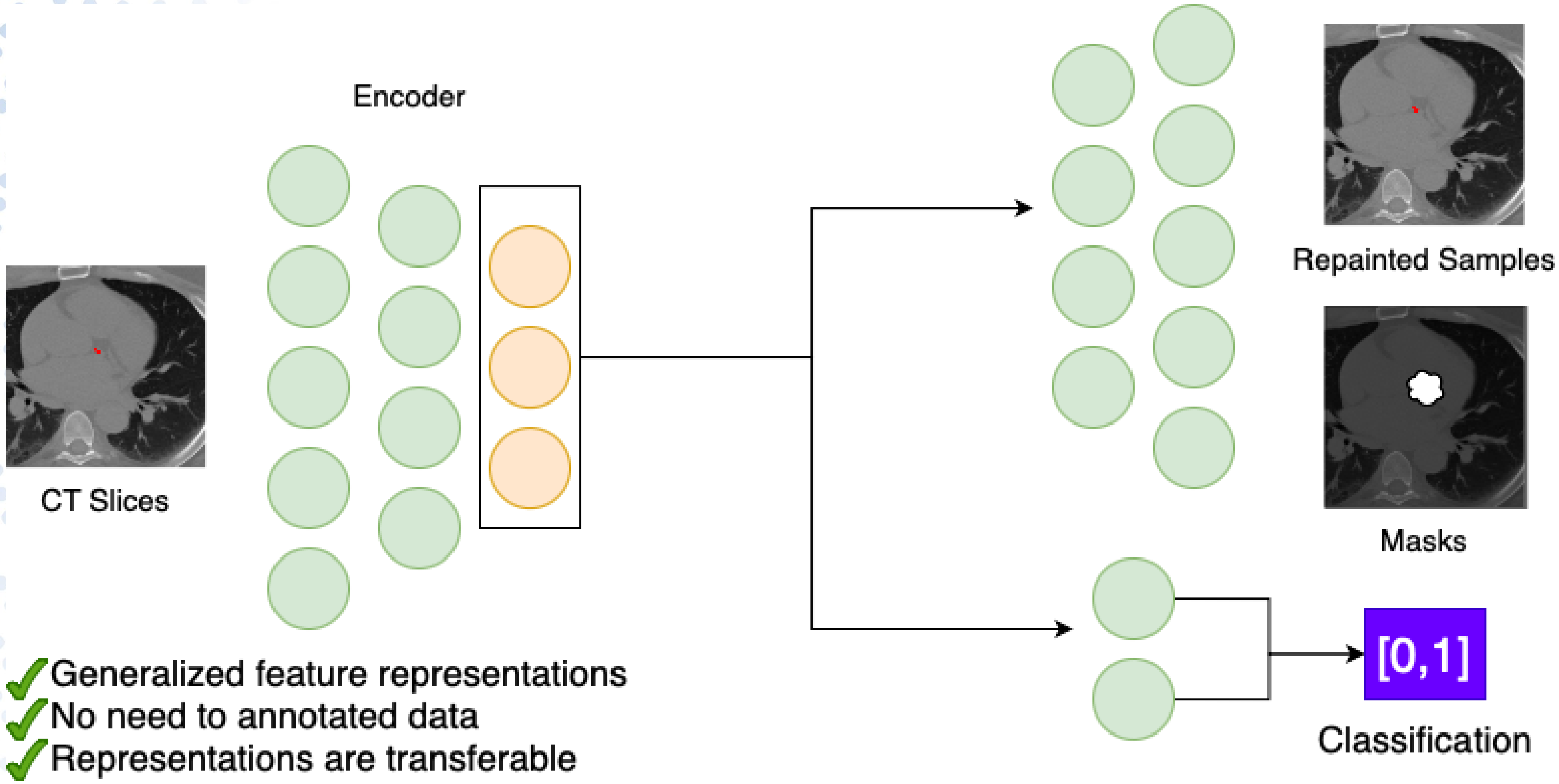
Transformer Encoder

$$
\begin{aligned}
Q &= X \times W^q, \quad W^q \in \mathbb{R}^{c\times d},\\
K &= X \times W^k, \quad W^k \in \mathbb{R}^{c\times d},\\
V &= X \times W^v, \quad W^v \in \mathbb{R}^{c\times d},
\end{aligned}
$$

$$
\mathrm{Attention}(Q, K, V) = \mathrm{softmax}\left(\frac{QK^T}{\sqrt{D_K}}\right)V = AV.
$$

SELF-SUPERVISED LEARNING

ADVANTAGES OF CONTRASTIVE LEARNING



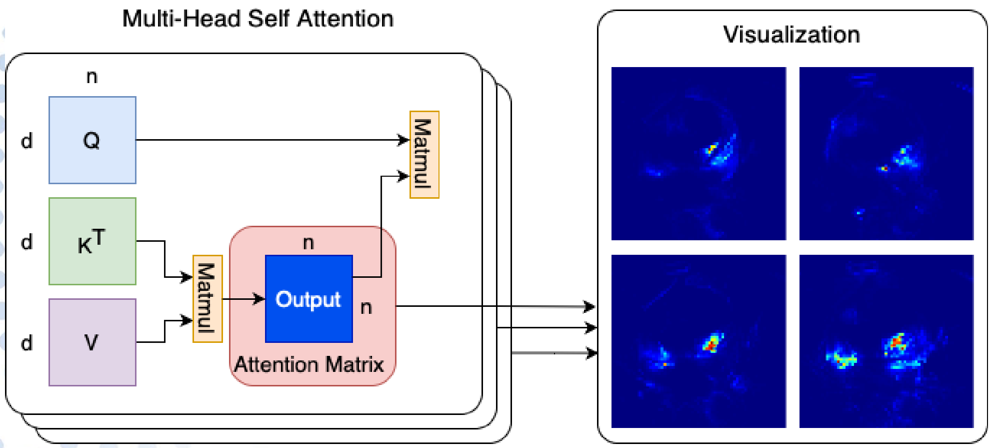
SELF-SUPERVISED LEARNING

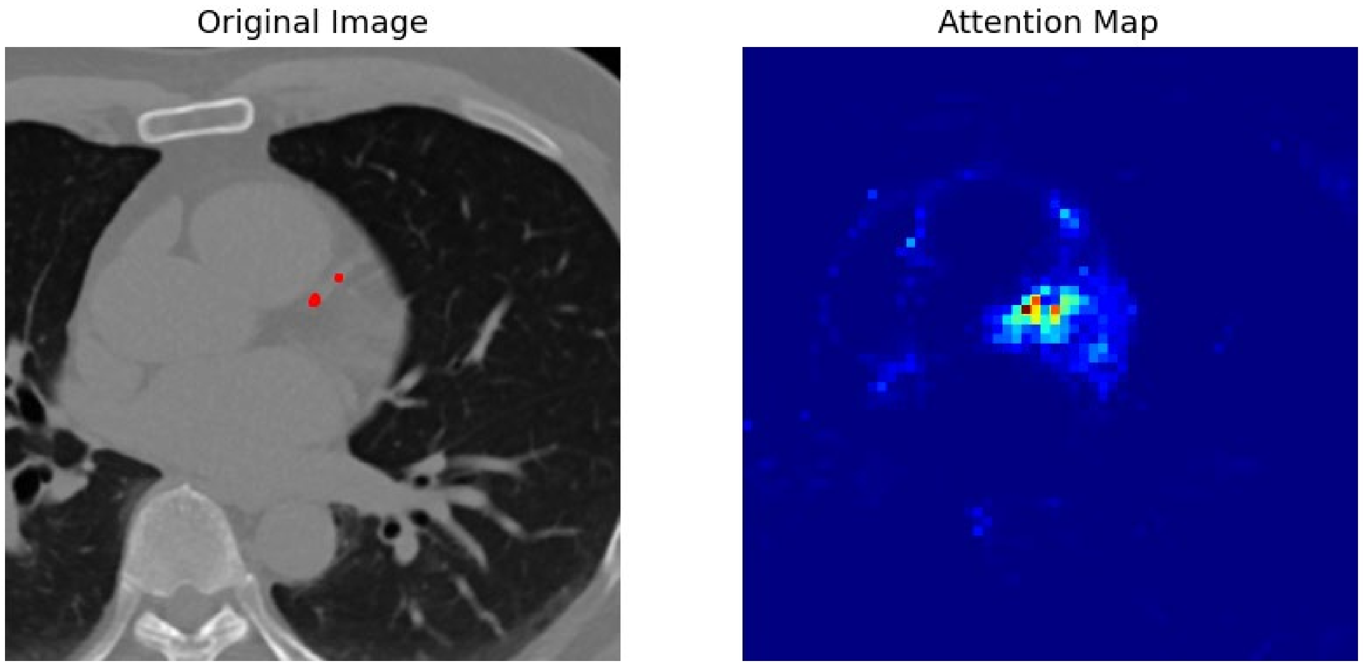
VISION TRANSFORMERS (VIT)

SELF-SUPERVISED LEARNING

DINO

Feature Visualization





FOUNDATIONAL MODELS

SELF-SUPERVISED LEARNING

Main purpose: Generating representations

Trained with Large Scale Datasets.

Google CT is trained with ~500K CT Slices

Foundational Model Variations:

- Vision Foundational Models (**DINO**, Stable Diffusion, SAM)
- Language Foundational Models (ChatGPT, Claude, LLaMa)
- Multi-Modal Models or **Vision Language Models** (CLIP, Gemini, GPT-4, DALL-E)

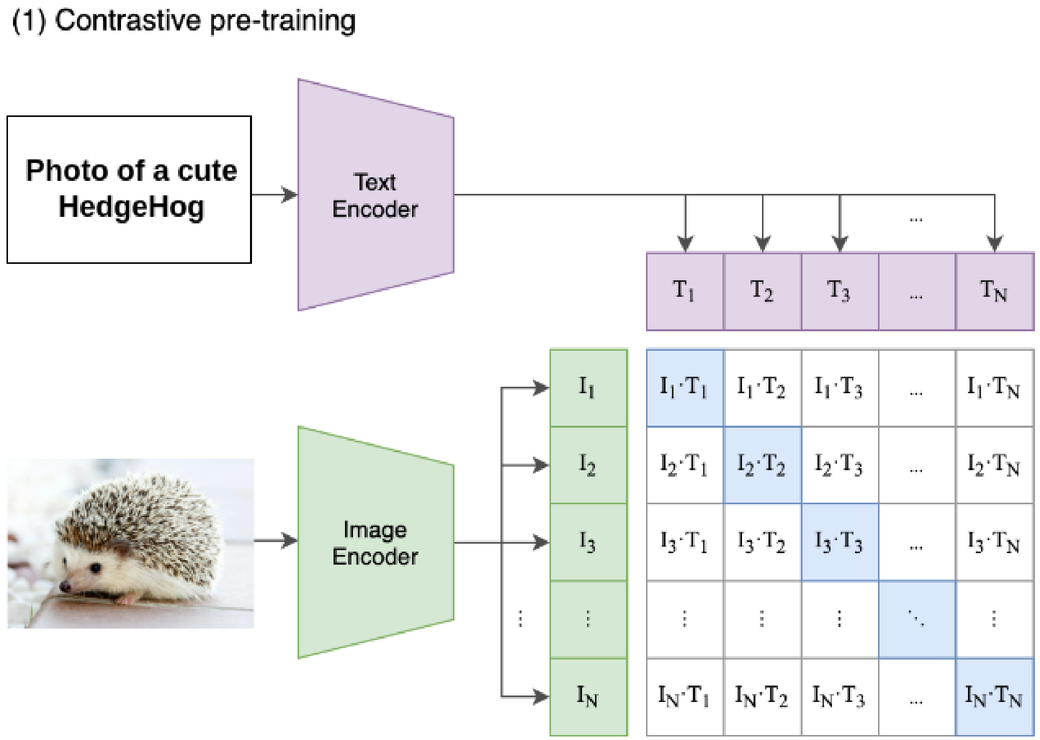
DINO foundational model trained with 142 million images.

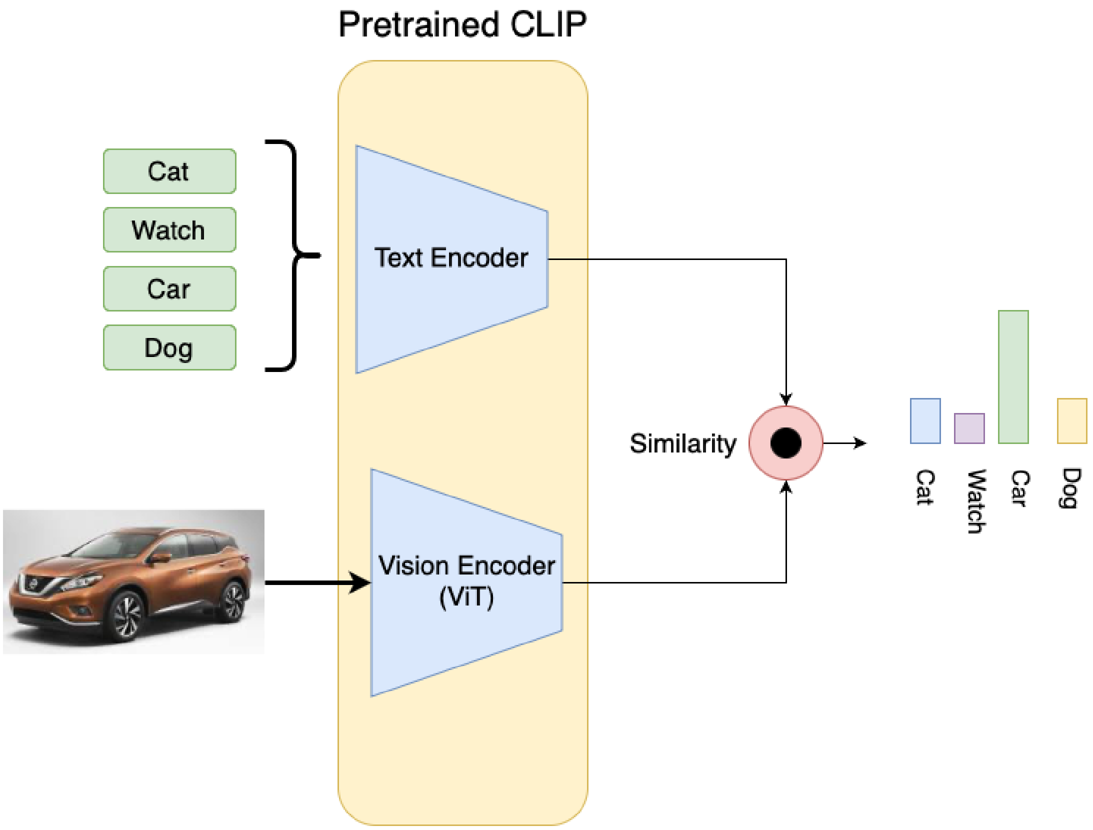
FOUNDATIONAL MODELS

SELF-SUPERVISED LEARNING

Multi-Modal Foundational Models

The most famous MMFM: CLIP Model
Trained with 400 Million Images

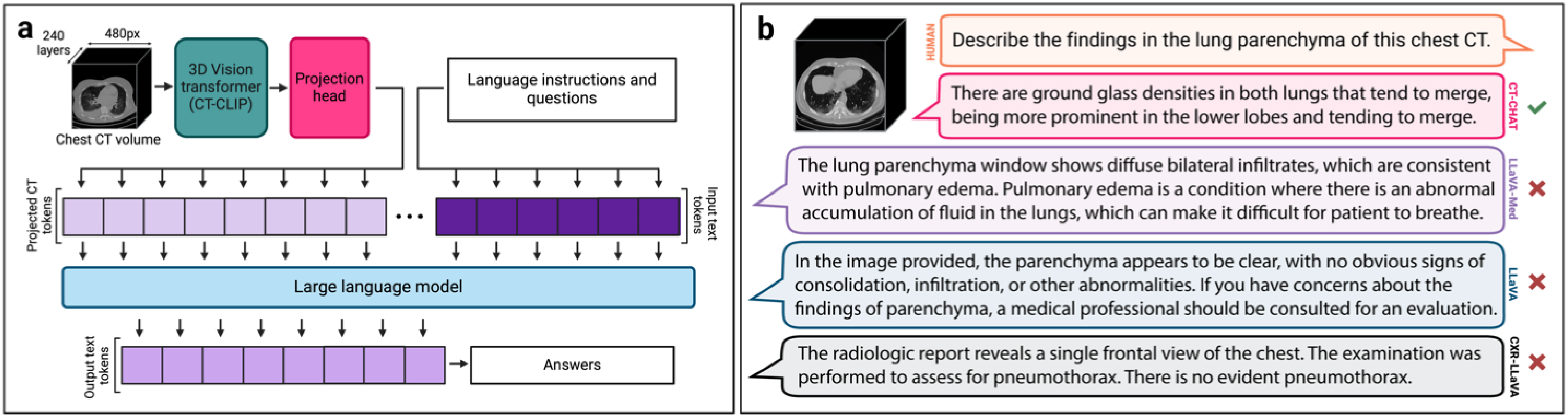




FOUNDATIONAL MODELS

SELF-SUPERVISED LEARNING

Multi-Modal Foundational Models

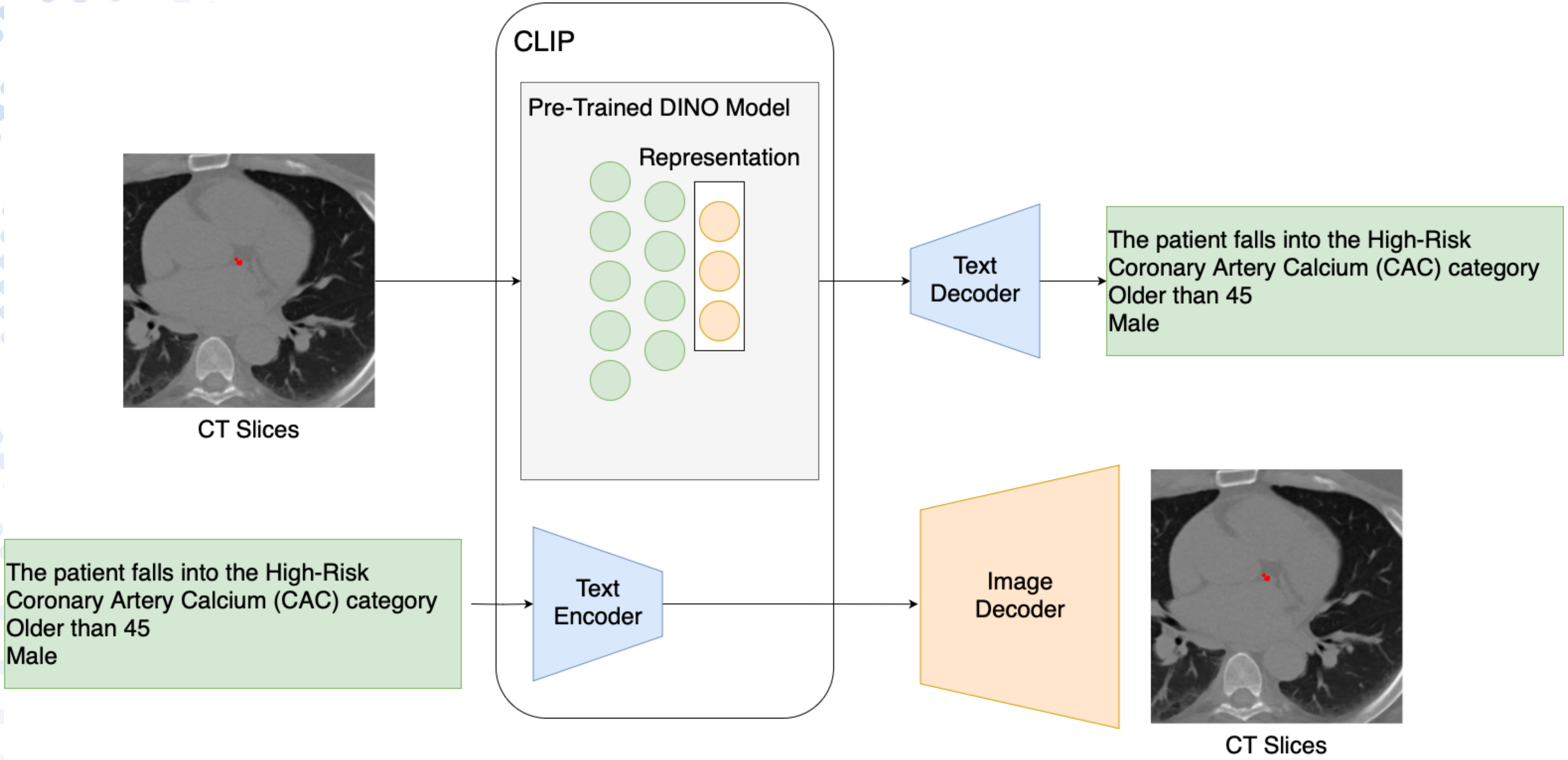


General working principle of a vision-language model [4]

FOUNDATIONAL MODELS

SELF-SUPERVISED LEARNING

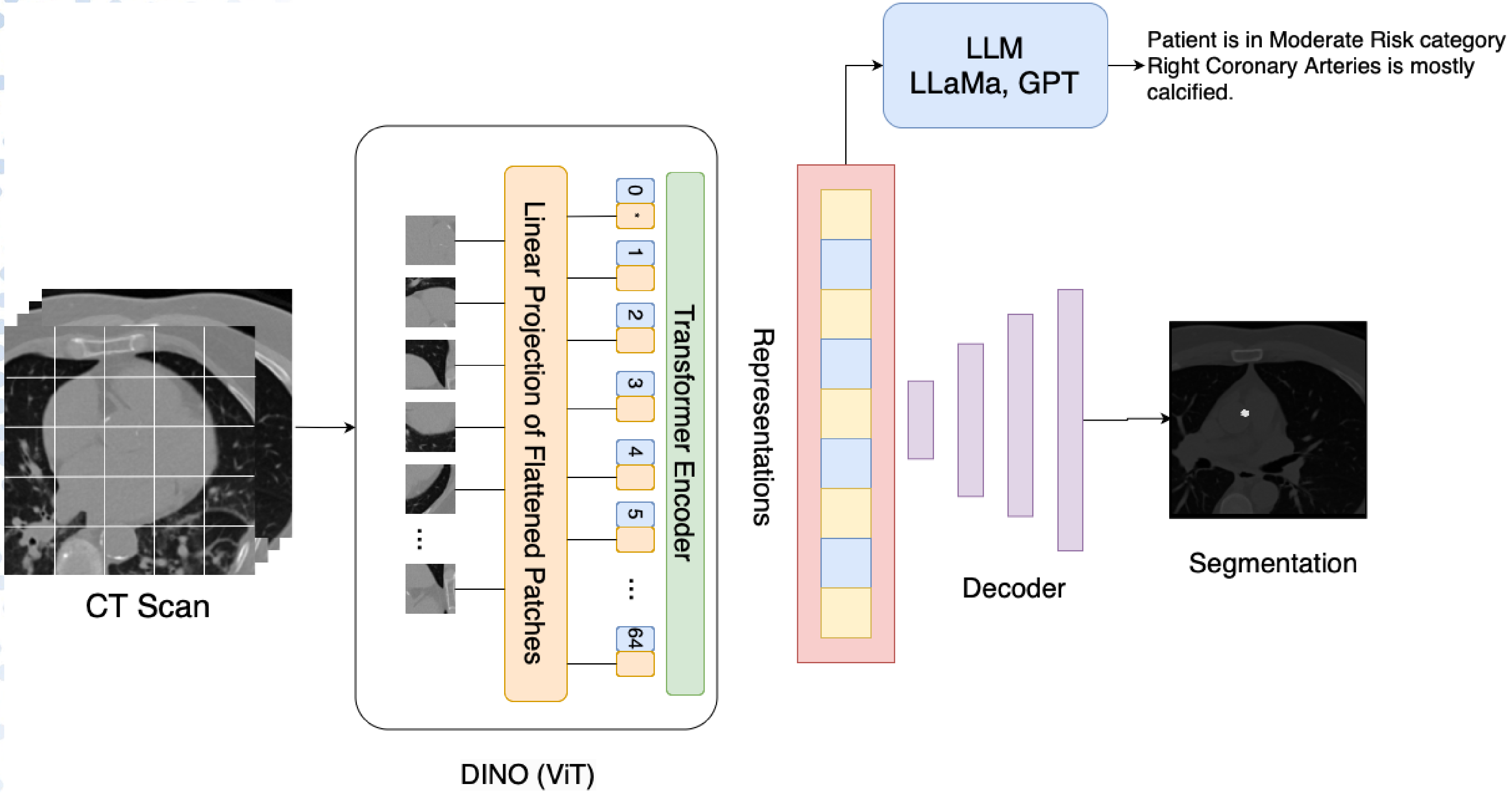
Multi-Modal Foundational Models (Vision Language Models)



FOUNDATIONAL MODELS

SELF-SUPERVISED LEARNING

Multi-Modal Foundational Models (Vision Language Models)



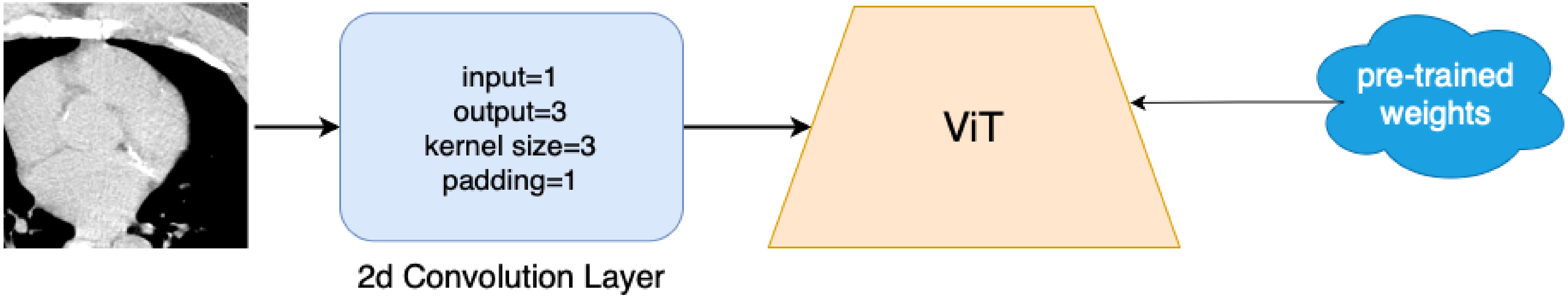
FOUNDATIONAL MODELS: OUR INNOVATIONS AND APPLICATIONS

DINO -LG (LABEL GUIDED SELF-DISTILLATION WITH NO LABELS)

Pre-trained weights are compatible with RGB images.

2d convolution layer applied to convert from single channel to 3 channels.

It makes possible to use pre-trained weights, provided by Facebook



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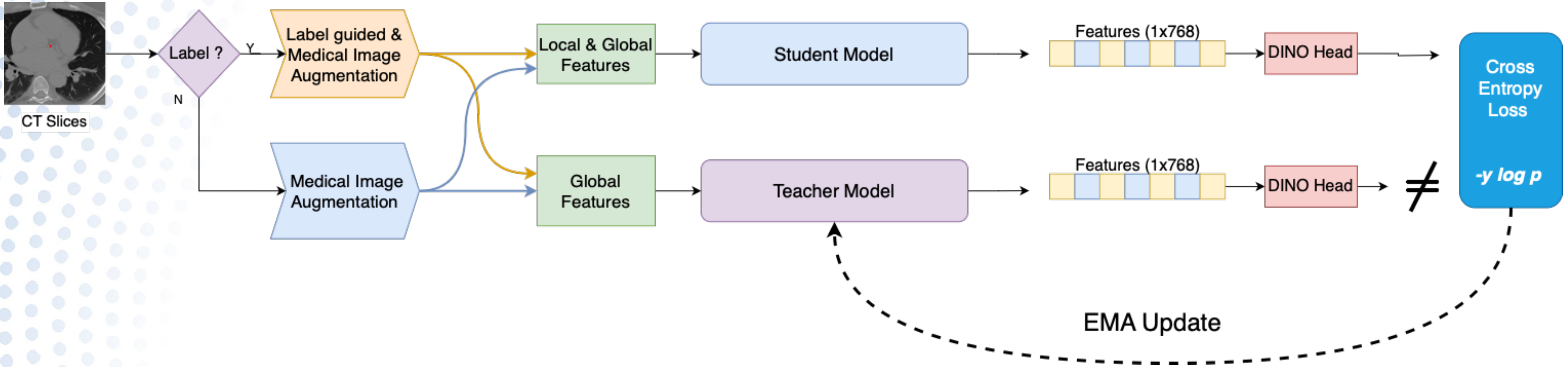
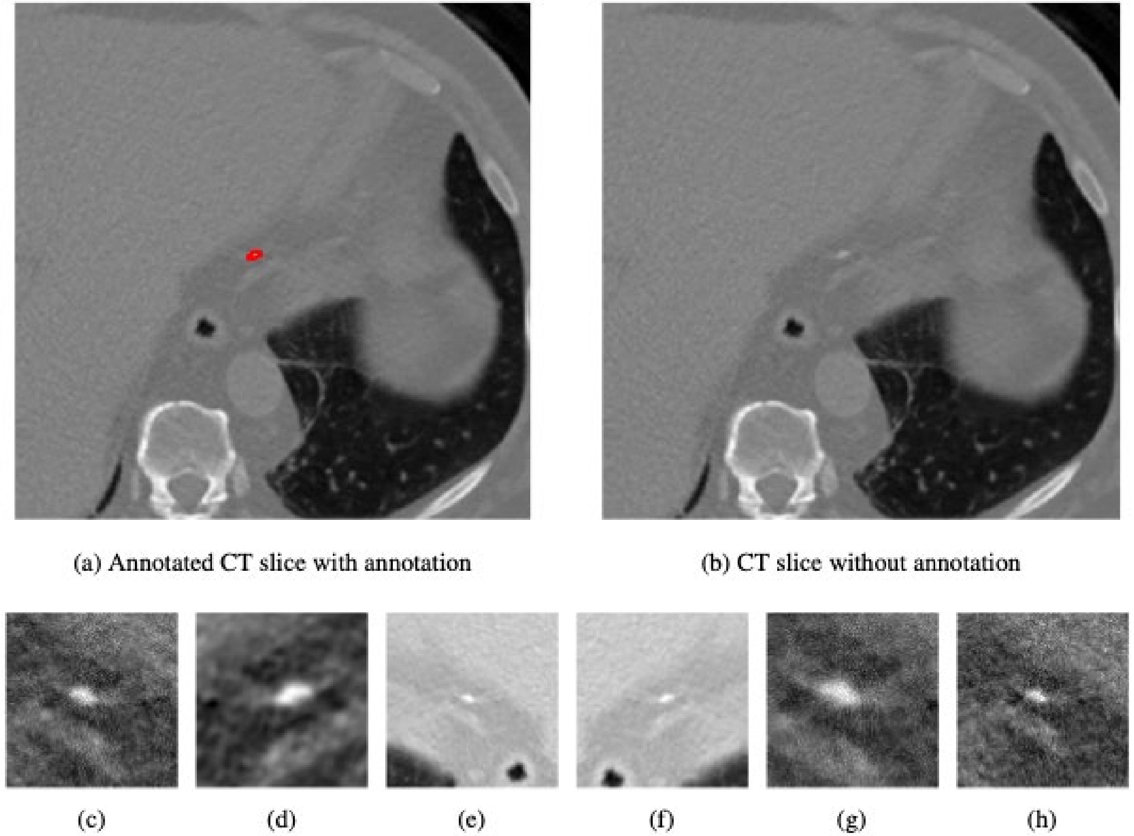
DINO -LG (LABEL GUIDED SELF-DISTILLATION WITH NO LABELS)



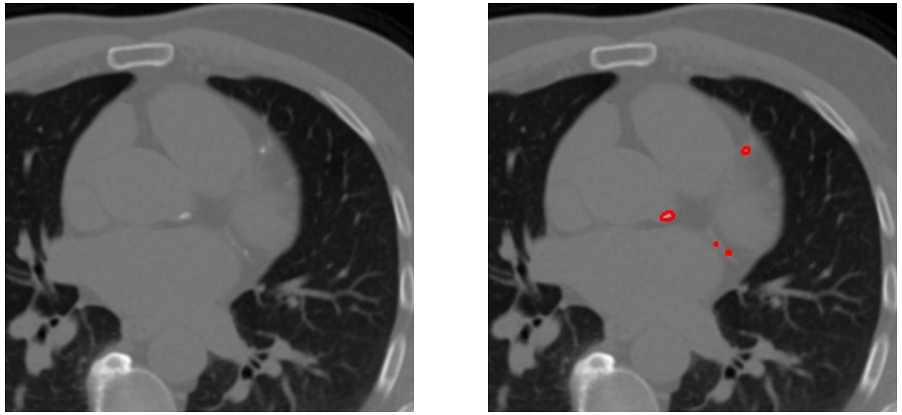
Model Name	ViT Type	# Random Local Crops	# Guided Local Crops	Augmentation	# Epochs
DINO-LG	ViTb8	12	4	Medical	150
DINO	ViTb8	16	0	Medical	150

FOUNDATIONAL MODELS: OUR INNOVATIONS AND APPLICATIONS

DINO -LG (LABEL GUIDED SELF-DISTILLATION WITH NO LABELS)

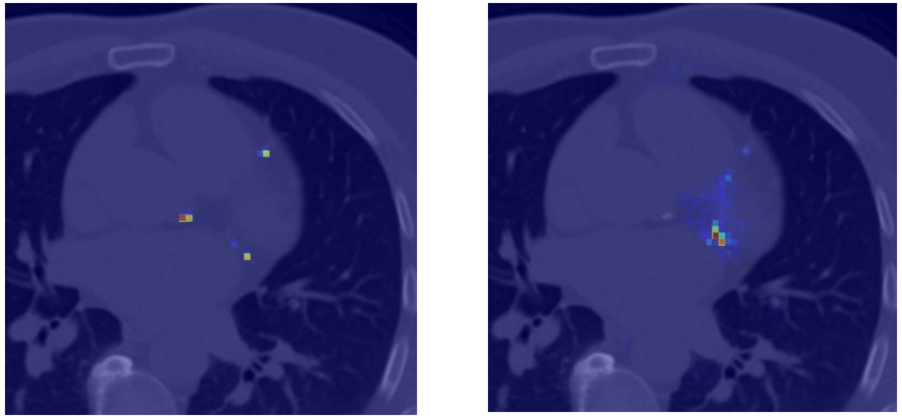


Label guided local crops from c to h



Original Image

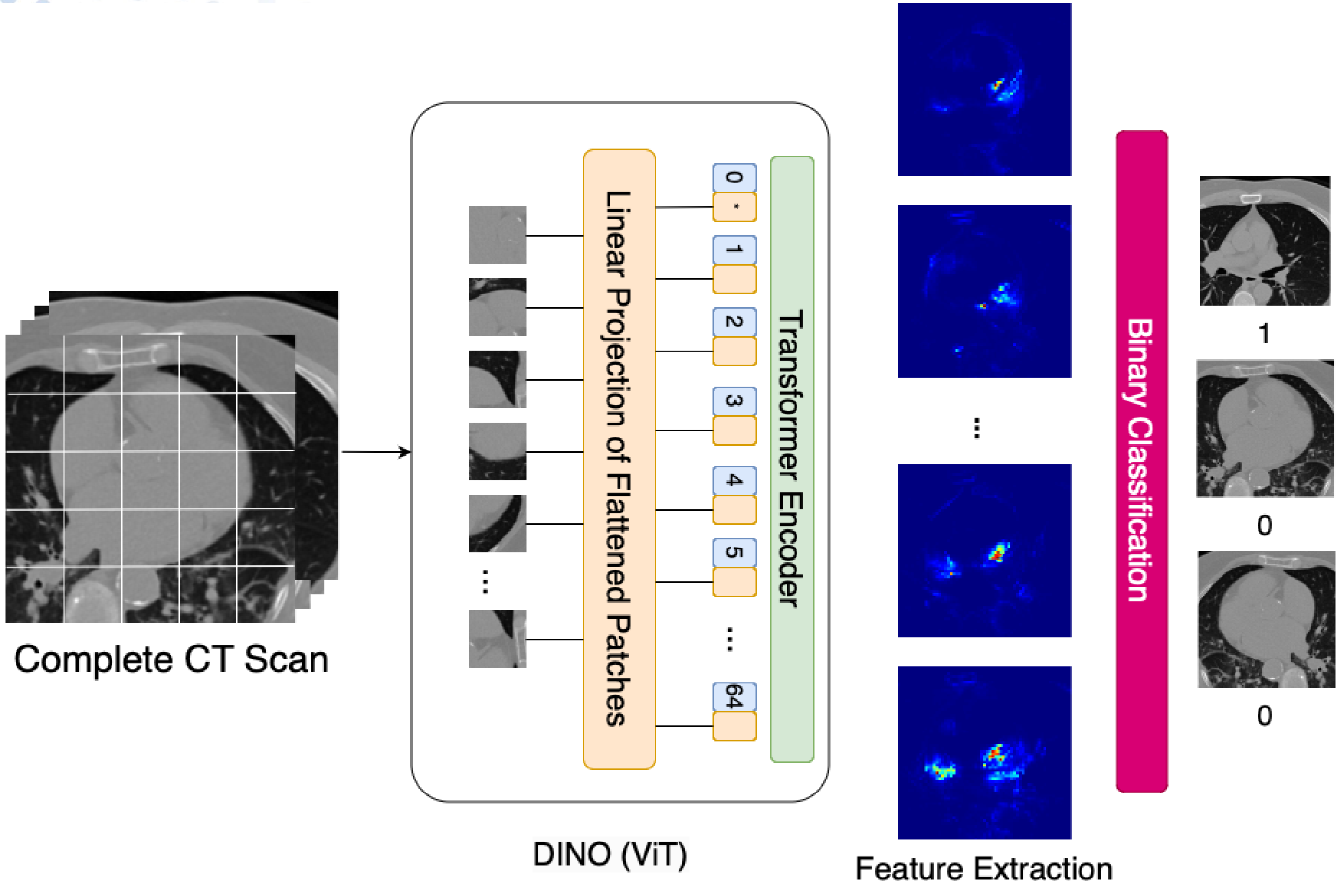
Masked Image

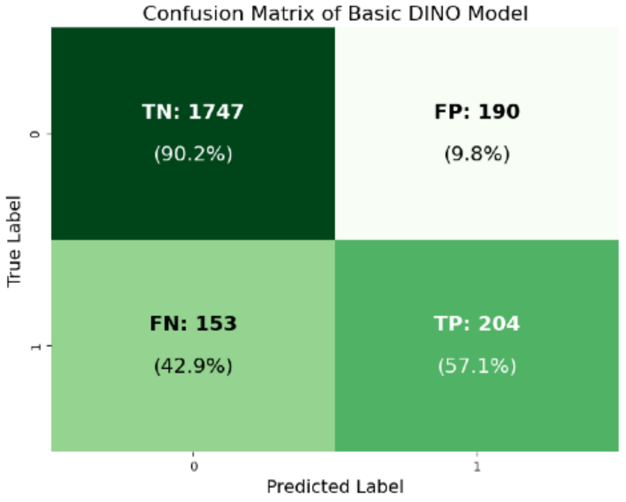


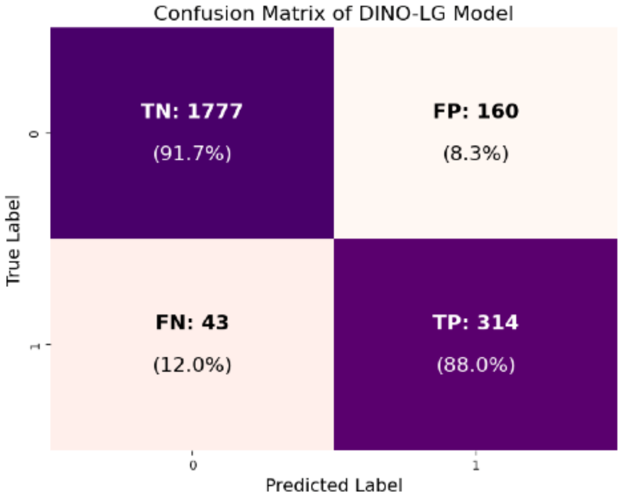
DINO-LG & Standard DINO Attention Map

FOUNDATIONAL MODELS: OUR INNOVATIONS AND APPLICATIONS

DINO -LG (LABEL GUIDED SELF-DISTILLATION WITH NO LABELS)







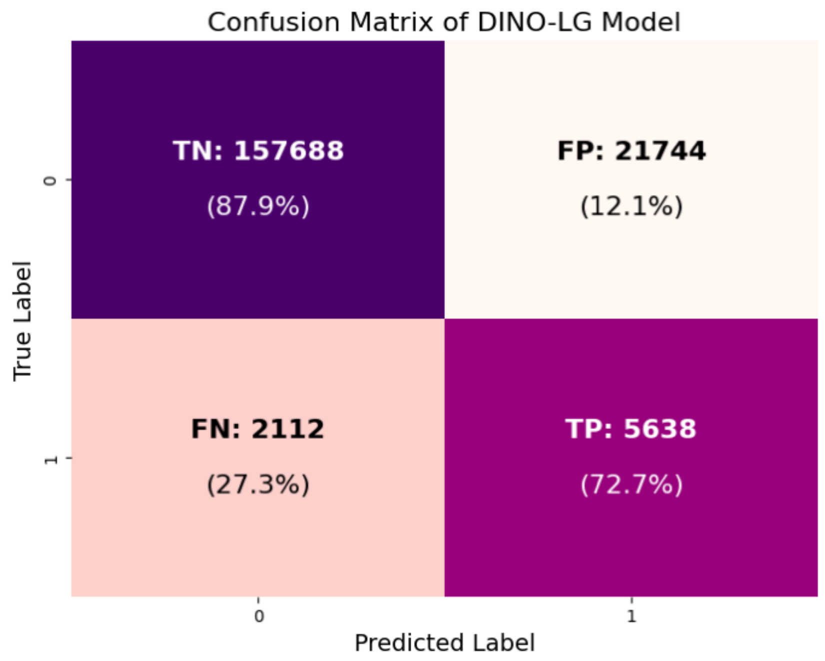
FOUNDATIONAL MODELS: OUR INNOVATIONS AND APPLICATIONS

DINO -LG (LABEL GUIDED SELF-DISTILLATION WITH NO LABELS)

Total Case: 3100
Number of CT slices: 191,457
Annotations: 8424

DINO model is trained with publicly available dataset COCA chest CT scans which provided by Stanford.

DINO model is tested directly on Heartlens dataset.



Classification results, conducted on UK Heartlens dataset

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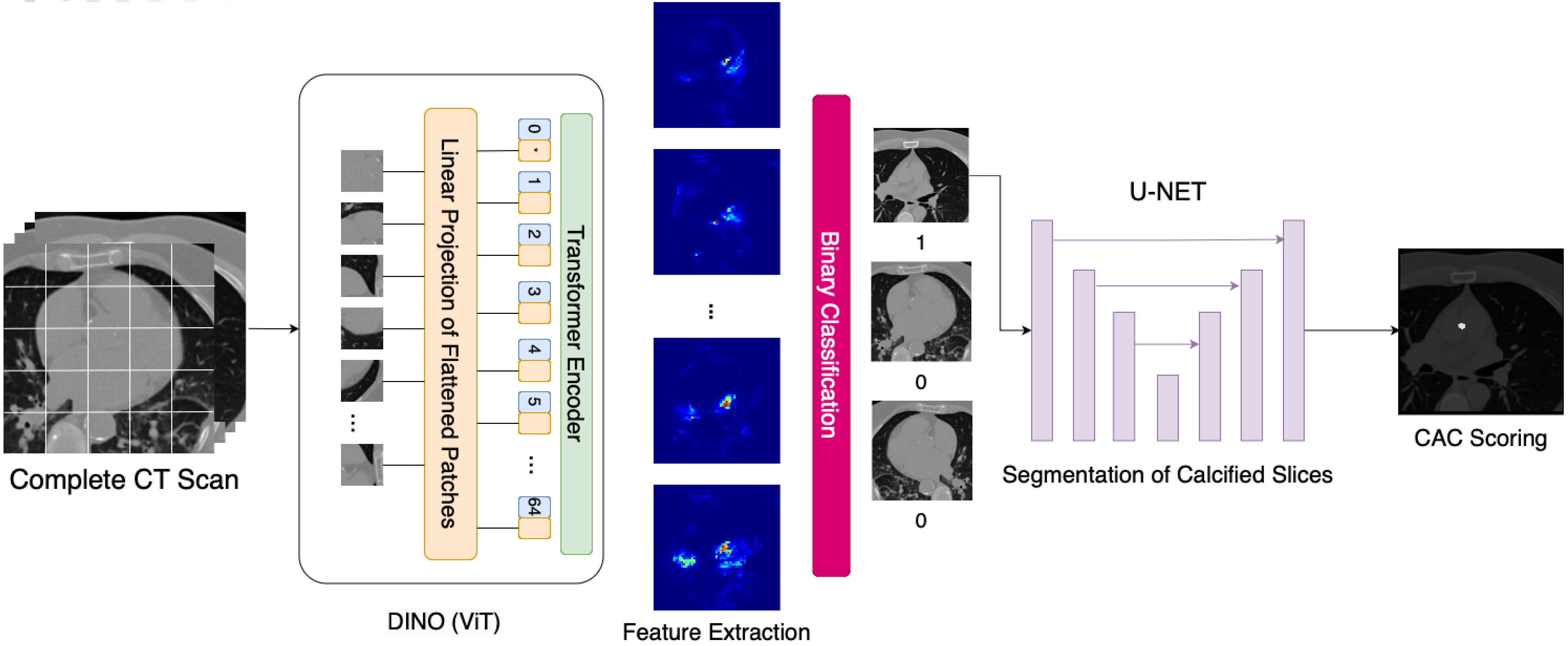
DINO -LG (LABEL GUIDED SELF-DISTILLATION WITH NO LABELS)



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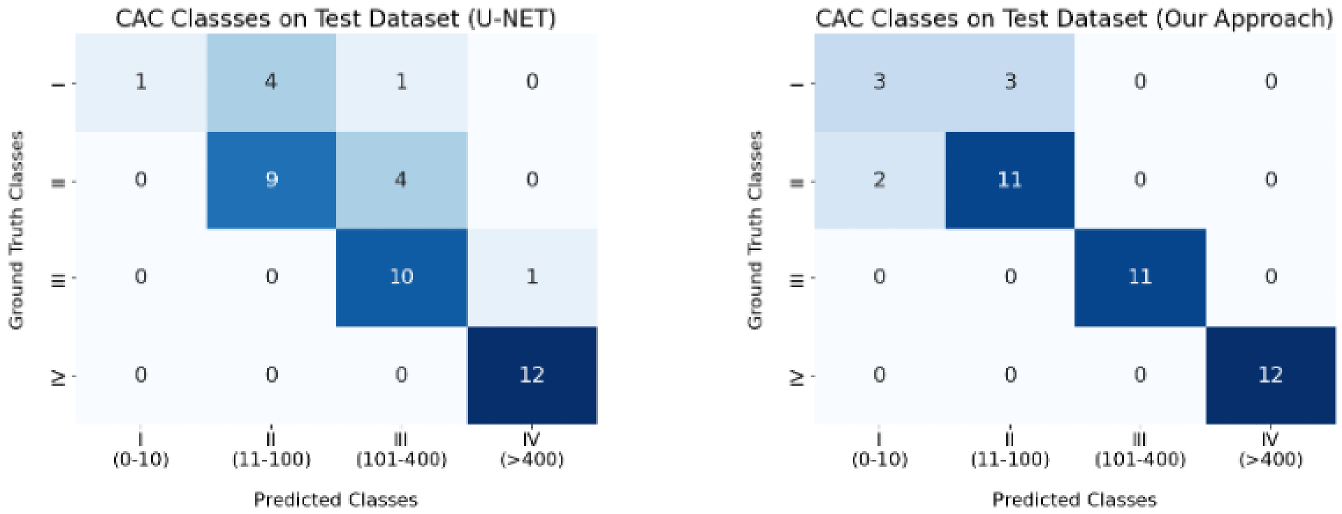
DINO -LG (LABEL GUIDED SELF-DISTILLATION WITH NO LABELS)



(a) Confusion Matrix for CAC Prediction using standalone U-NET

(b) Confusion Matrix for CAC Prediction our proposed system

CAC Scoring and risk assessment results of overall architecture

DINO-LG: A Task-Specific DINO Model for Coronary Calcium Scoring
https://arxiv.org/abs/2411.07976

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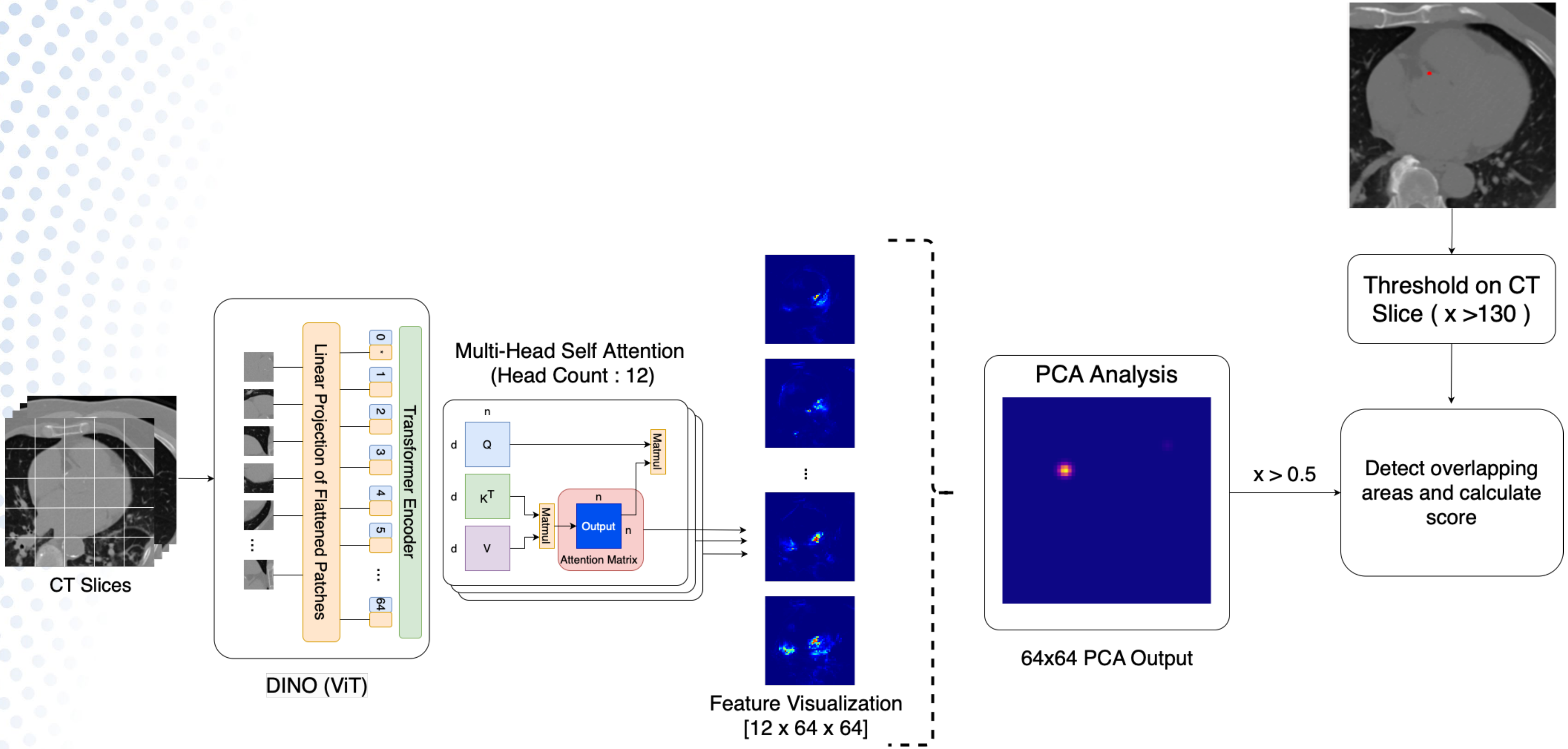
DINO -LG (LABEL GUIDED SELF-DISTILLATION WITH NO LABELS)



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THANKS

[1] V. Sandfort and D. A. Bluemke, “CT calcium scoring. History, current status and outlook,” Diagnostic and Interventional Imaging, vol. 98, no. 1. Elsevier BV, pp. 3–10, Jan. 2017. doi: 10.1016/j.diii.2016.06.007.

[2] D. Shreya et al., “Coronary Artery Calcium Score - A Reliable Indicator of Coronary Artery Disease?,” Cureus. Springer Science and Business Media LLC, Dec. 03, 2021. doi: 10.7759/cureus.20149.

[3] J. Gui et al., “A Survey on Self-supervised Learning: Algorithms, Applications, and Future Trends,” 2023, arXiv. doi: 10.48550/ARXIV.2301.05712.

[4] I. E. Hamamci et al., “Developing Generalist Foundation Models from a Multimodal Dataset for 3D Computed Tomography,” 2024, arXiv. doi: 10.48550/ARXIV.2403.17834.