Automated Coronary Calcium Scoring using U-Net Models through Semi-supervised Learning on Non-Gated CT Scans

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Abstract—Every year, thousands of innocent people die due to heart attacks. Often undiagnosed heart attacks can hit people by surprise since many current medical plans don’t cover the costs to require the searching of calcification on these scans. Only if someone is suspected to have a heart problem, a gated CT scan is taken, otherwise, there’s no way for the patient to be aware of a possible heart attack/disease. While nongated CT scans are more periodically taken, it is harder to detect calcification and is usually taken for a purpose other than locating calcification in arteries. In fact, in real time coronary artery calcification scores are only calculated on gated CT scans, not nongated CT scans. After training a unet model on the Coronary Calcium and chest CT’s gated scans, it received a DICE coefficient of 0.95 on its untouched test set. This model was used to predict on nongated CT scans, performing with a mean absolute error (MAE) of 674.19 and bucket classification accuracy of 41% (5 classes). Through the analysis of the images and the information stored in the images, mathematical equations were derived and used to automatically crop the images around the location of the heart. By performing semi-supervised learning the new cropped nongated scans were able to closely resemble gated CT scans, improving the performance by 91% in MAE (62.38) and 23% in accuracy.

I. INTRODUCTION

Heart disease and stroke is the leading cause of death worldwide and its mortality rate keeps increasing as the years pass by. According to CDC, one death in every four deaths occurs from heart disease, around 659,000 people each year [4]. Heart stroke is often not predicted early enough, making heart attacks very dangerous. They are hard to detect early on, since radiologists are not required to search for calcification in the arteries when examining nongated CT scans. Current medical plans don’t cover this search and as a result there is no early indicator for a future heart problem (heart attack) [5].

- In the United State (2019), someone had died of heart stroke every 3 minutes 30 seconds [12].
- 45% of heart attacks are silent, otherwise known as undetected heart disease [3].
- 325,000 US citizens die due to sudden cardiac death [13].
- Silent Heart Disease is common amongst the elderly and athletes and is caused when no visible symptoms are shown.
  - One of the best tests for Silent Heart Disease is scans such as Nongated and Gated CTs [2].
- The buildup of calcium is one of the earliest indicators of heart disease.

Heart attacks occur when blood clots form in the heart and the tissues begin to receive less oxygen, stopping the heart from pumping blood to the rest of the body. On CT scans, blood clots (calcification) appear as opacity on the scan (both gated and nongated CTS). CAC or Coronary artery calcium scoring is often performed and measured into 5 classes (I, II, III, IV, V) [1]. A healthy patient with no calcification in the coronary arteries would be classified as a I. This number is used to measure how dangerous of a situation the patient is in, I being healthy and V representing extreme danger.

Calcium Scans are not covered by most insurance plans. Most plausibly due to the newness of this test as it has only recently been introduced into the field of detection/segmentation of calcification in the arteries. As of now, it needs to be requested to be checked by your doctor [5].

Two types of scans are taken of the chest/heart. One is a Gated CT scan, and the other is a Non Gated CT scan. Nongated CTs are more prominently taken as they are used for more purposes than one, whereas Gated CTs are only taken for the purpose of identifying calcification [7]. Unfortunately that is a paradox of its own as gated CTs are only taken when there has already been an indicator of bad health in the past or suspicion of a heart disease.

Fig. 1. Gated scans are less predominantly taken in the medical field as it serves a single purpose of identifying calcification

Fig. 2. Nongated scans are predominantly taken in the medical field as it can be used for many different purposes.
TABLE I
NONGATED DICOM INFO

| Element                        | Value                       | Diameter (NG) |
|--------------------------------|-----------------------------|---------------|
| (0018, 1100) Reconstruction Diameter DS: | '301.0'                     |               |
| (0018, 9313) Data Collection Center (Patient) FD: | [0.2939453125, -154.2060546875, -356.7] | DCC (NG)      |
| (0018, 9318) Reconstruction Target Center (Patient) FD: | [13.2939453125, -154.2060546875, -356.7] | RTC (NG)      |
| (0028, 0030) Pixel Spacing DS: | [0.587890625, 0.587890625] | PS (NG)      |

TABLE II
GATED DICOM INFO

| Element                        | Value                       | Diameter (G) |
|--------------------------------|-----------------------------|---------------|
| (0018, 1100) Reconstruction Diameter DS: | '205.0'                     |               |
| (0018, 9313) Data Collection Center (Patient) FD: | [0.2001953125, -178.2998046875, -297.75] | DCC (G)      |
| (0018, 9318) Reconstruction Target Center (Patient) FD: | [49.2001953125, -178.2998046875, -297.75] | RTC (G)      |
| (0028, 0030) Pixel Spacing DS: | [0.400390625, 0.400390625] | PS (G)      |

II. RELATED WORK

Currently there is little amounts of research done on the segmentation of calcification on nongated CT scans due to the lack of data publicly available to use. A research paper by Roman Zeleznik et al. trained a complex network on both gated and nongated but only showed results on gated scans as they believed in practice CAC scores are not made off of nongated scans [14]. A Stanford cs230 group performed a project on the Stanford COCA dataset training a unet model on gated scans [9]. Another research project was done on this dataset along with a private dataset with more information about correlations and masks [1].

A group of students from Stanford trained a unet model on the gated CT scans, publishing their work on github [6]. We were able to use their research and improve their results by 76.8%. It is clear that for all segmentation models in the field of healthcare the most common and best performing network is unet. Most research is done on gated CTs since the data is much more prevalent which is also reflected in the dataset provided by Stanford and used in this research [11]. The best performing model on gated CT scans has a DICE coefficient of 0.739 by the Stanford cs230 group [9].

III. METHOD

A. Problem Formation

Searching the location of calcification in the arteries is a segmentation problem. The input of this model is a 2D CT scan taken from a volume of 2D scans making a full CT for a patient, and the output of the model is the segmentation of calcification in the 2D nongated scan. We use focal DICE loss during training.

Since each of these scans were saved as DICOM files there was more information apart from the pixel data give about the scans (Table I & Table II) [10]. We were able to use this information to manipulate the non gated scan to closely replicate the gated scan in terms of the location it was looking at. Furthermore the amount of data was lacking in the nongated CT scans making it very difficult to create a reliable supervised model from the nongated dataset, forcing the training to be done on the gated CT scans. We hypothesized the model would perform better on these manipulated nongated scans as it was trained on the more abundant, gated images.

B. Model Architecture and Training

The model was based off the U-net architecture with an input sizes of 512x512x1 [8]. The unet architecture is the same as that stated in the paper published by the CS230 Stanford group [9]. We retrained this model on the gated data with the Y as the real mask segmentations. We then began the cropping process of the nongated data to replicate the structure of the gated data. Since the unet model was trained on data that was centered around the heart we wished to do the same with the cropping of the scans (Fig 3). The cropping was done through a system of equations.

\[
\Delta x_{n-g} = DCC(NG)(x) - DCC(G)(x) \\
\Delta y_{n-g} = DCC(NG)(y) - DCC(G)(y) \\
r = \frac{\text{diameter}(G)/2}{PS(NG)} \\
\Delta x = \frac{(RTC(G)(x) + \Delta x_{n-g} - RTC(NG)(x))}{PS(NG)} \\
\Delta y = \frac{(RTC(G)(y) + \Delta y_{n-g} - RTC(NG)(y))}{PS(NG)} \\
x = 256 + \Delta x - r \\
y = 256 + \Delta y - r
\]

With DICOM files the origin is randomized and it is not possible to find out where the origin is located, meaning it...
is not the same for different scans. We were searching for a constant point to be able to create comparisons. The data collection center is the center of the machine in which the patient was put in. This point is constant when the machine diameter is the same. When analyzing the data points it was found that the size of the machine was constant for all scans taken, it was not known whether this meant that the same machine was used or if it was taken in the same place, but it provided enough information to use the difference between data collection centers of gated and nongated scans for future calculation. The reconstruction data center is the center point of the scan, so it varies from scan to scan. Using the data collection center, we can find out the correlation between the two reconstruction centers and calculate the $\Delta x$ and $\Delta y$ from the nongated center which is 256,256 in a 512x512 size scan. This leads to the final calculation of finding the top leftmost point of the cropped image. We add each, $\Delta x$ and $\Delta y$, to 256 and subtract the radius which depends on the pixel spacing (mm) of the nongated images which is not a fixed number. The diameter of the gated scans is a constant value of 205 mm (Fig 4).

In real time, the gated images would not exist, so instead a fixed value is entered in replacement of the variables requiring (G). These fixed values were hand chosen based off the validation set. We analyzed the change in performance as the cropping variables changed. It was very slight change in performance as the calcification was still located in the middle of the scans versus the edges. Changing the Gated DICOM values rarely changed the location of the cropped scan, rather changed the edges and moved it slightly left or right. Table II shows the final G variables used.

### C. Datasets

The dataset used is called COCA - Coronary Calcium and chest CT’s [11]. The COCA dataset provided by Stanford contains both gated (700) and nongated CT scans (200). We split the data into 80% train, 10% dev, and 10% test for gated CT scans. The gated coronary CT has mask segmentations that show the location of coronary artery calcium in which slices of the 3d volume. The nongated CT scans contain the coronary artery calcium scores saved in an xml file. The images, both gated and nongated, are saved as DICOMs meaning extra information is available when reading the file. This information was very valuable identifying the location of the heart in the entire lung automatically. The main point(s) used was the data collection center and reconstruction center. To train the unet model, we tweaked the original parameters and changed their code to fit on the data better. We identified a few errors in their code which we had also changed when reproducing their results. We also performed upsampling on the few slices that contain calcification since the dataset was very imbalanced.

![Image](image-url)

**Fig. 4.** The figure to the above shows the different pieces of information given in the two tables previously shown. Every coordinate is in terms of mm. The data collection center is the point used to find the possible gated location in nongated image.

**Fig. 5.** The flowchart above depicts the process the model went through. It began by training on gated data and predicting on non gated data that was cropped.

Since there was a reliable amount of data for gated CT scans in comparison to nongated data, a model trained on gated CT scans would theoretically perform better. Furthermore the gated CT scans had the real masks locating which pixels contained calcification, whereas the nongated CT scans only had the final CAC (coronary artery calcification) score. Training a unet model on a small amount of 3d data with an output of 1 value can cause severe overfitting and a very biased model. We trained our base unet model on gated CT data and then predicted on cropped nongated data (fig 5)

## IV. RESULTS

### A. Metrics

The DICE loss was used to train unet models. Dice loss was very beneficial because it essentially puts a weightage on accurately segmenting a pixel with calcification over the more popular pixel without calcification. For regression models which we experimented with, we used the metric of mean squared error and mean absolute error. The y-value in the regression models was the CAC (coronary artery calcification) score. The CAC (coronary artery calcification) score is used to find out how much calcification is in the coronary arteries. As a comparison a healthy person would have a CAC score of 0. When using the segmentation unet model to see how well it was performing on nongated images, we mathematically calculated the score based on its segmentation prediction and
then compared it to its stored real CAC score. Another label used was the bucket scores which was automatically calculated from the predicted values. The bucket values are essentially used for the final medication for the patient to receive. There are 5 bucket values:

**Bucket 1**: score = 0 (healthy - no danger)
**Bucket 2**: 0 < score < 11 (precautions should be taken)
**Bucket 3**: 10 < score < 101 (seek med professional)
**Bucket 4**: 100 < score < 401 (heart attacks may be common)
**Bucket 5**: 400 < score (VERY DANGEROUS)

The buckets are more valuable than the real CAC score as medication and future actions are taken based off of the danger level rather than the exact amount of calcification in the arteries.

### B. Final Results

Confusion matrices represent the models performance on predicting the accurate bucket or danger level for the patient. This information should be as accurate as possible as it determines the next steps in medication. The green represents the accurate bucket in which a 100% efficient model would classify all of the images with that class into. The darker pink is a more severe error (2 incorrect images), the lighter pink refers to 1 incorrect classified scan. An optimal model would have all scans accurately classified, with no pink/dark pink in surrounding areas.

#### TABLE III
**REAL CAC BUCKET VS. PREDICTED CAC BUCKET ON GATED CT (TEST)**

| Real CAC Bucket | Predicted CAC Bucket |
|-----------------|----------------------|
| Real CAC Bucket | Predicted CAC Bucket |
| 1               | 1 0 0 0 0 0         |
| 2               | 0 0 2 0 0 0         |
| 3               | 0 0 0 10 0 0        |
| 4               | 0 0 0 0 6 0         |
| 5               | 0 0 0 0 0 4         |

Table III is the confusion matrix of the retrained Unet model tested on the Gated images test set consisting of 22 patients. This model had a 100% accuracy in terms of class prediction but this may not be a perfect representation of its accuracy since it is not mentioned what pids the original Unet model was trained on (Table III).

#### TABLE IV
**REAL CAC BUCKET VS. PREDICTED CAC BUCKET ON NONGATED CT**

| Real CAC Bucket | Predicted CAC Bucket |
|-----------------|----------------------|
| Real CAC Bucket | Predicted CAC Bucket |
| 1               | 1 2 3 4 5           |
| 2               | 0 0 0 0 0           |
| 3               | 0 0 0 0 0           |
| 4               | 0 0 0 0 0           |
| 5               | 0 0 0 0 0           |

Table IV is the confusion matrix of the retrained Unet model tested on the full Nongated images test set consisting of 22 patients. This model had a 41% accuracy (20% > than random model) in terms of class prediction.

#### TABLE V
**REAL CAC BUCKET VS. PREDICTED CAC BUCKET ON CROPPED NONGATED CT**

| Predicted CAC Bucket |
|----------------------|
| 1 1 1 1 1 0 |
| 2 0 0 0 0 0 |
| 3 1 0 1 0 0 |
| 4 0 0 1 2 0 |
| 5 0 0 0 0 4 |

Table V is the confusion matrix of the retrained Unet model tested on the Cropped Nongated images test set consisting of 22 patients. This model had a 64% accuracy in terms of class prediction.

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As the unet model is trained on gated CT it performs the best on gated CTs. When plotting the Predicted CAC score
versus the Real CAC score the optimal line is $y=x$. Fig 6 shows this optimal line as most of the data points are near perfect on test set of gated CT scans. In contrast, the model predicts terribly on uncropped nongated CT scans (Fig 7). The points seem to be randomized and no correlation can be seen. On the cropped nongated CT scans the performance significantly increased. The line of best fit displayed on Fig 8 is near the optimal line, and a slight linear positive correlation can be seen. Comparison between the model performance on full nongated versus cropped nongated can be seen in figure 9 with the obvious lower mean absolute error with cropped nongated scans.

C. Analysis

**TABLE VI**

|                  | Gated | Nongated | Cropped Nongated |
|------------------|-------|----------|------------------|
| **MAE (Total)**  | 114.33| 674.19   | 62.38            |
| **MAE (w/o outliers)** | 25.12 | 93.82   | 51.05            |
| **# of outliers** | 2     | 5        | 2                |

After re-training the Unet model on the Gated scans we began to analyze its performance on different types of images, specifically nongated and cropped nongated. We hypothesized the model would perform better on cropped nongated images because it replicates the format of the gated images more closely. Our results proved this hypothesis. The gated and nongated image inputs are not comparable since it is not known whether these patients are the same people or different. It is possible that the gated data we tested the unet model on was used as training or validation data as it was not mentioned in their work which patient ids were in the three different sets of data. Furthermore this is noncomparable since gated and nongated are two different types of scans, where gated is meant for the purpose of finding calcification whereas nongated can be used for other things making it slightly more difficult to find calcification on it. Comparing the cropped vs uncropped model, there is a big difference in overall MAE, 612 (Table VI). MAE stands for the mean absolute error therefore needing to calculate it without outliers as they can put a large effect on it. There seem to be a greater number of outliers when the dataset used as input was the full nongated image. A possibility for this is that many medical devices or sudden white spaces appear in the black void of the nongated scans causing further misconception. This model can be used in medical fields to try and automatically alert patients of the possibility of having calcification in their heart without having to pay the extra medical fee for its search. Below is a table representing the performance on different classification models on the buckets (Table VII).

**TABLE VII**

|                  | Gated | Nongated | Cropped Nongated |
|------------------|-------|----------|------------------|
| **Recall**       | 1.00  | 0.59     | 0.79             |
| **Precision**    | 1.00  | 0.44     | 0.6              |
| **F1 Score**     | 1.00  | 0.52     | 0.68             |

The cropped images proved to be more useful to the model because the calcification is more easily visible since the size of the heart significantly increased. The cropped portion removed all the irrelevant information making it easier for the model to focus on possible real calcification versus information that may refer to something else. Further evidence of this statement is found when looking at the number of pixels the model predicts on cropped (enlarged) images being greater than on uncropped images.

When the amount of calcification is heavy it does not perform well as shown in the leftmost picture (Fig 10). The other three images depict how the model is not able to accurately find calcification and latches onto non-heart items. The model focus on areas outside the heart which makes sense as it is still trying to locate abnormal opacity. The images are not similar to the ones it trained on.

The leftmost image still performs well, no performance is lost, but more information is gathered since the model gets a
better idea where the calcification might be and is not confused
with other pieces of irrelevant information. Unfortunately there
are still a few bad images such as the third picture from the
left where the model predicts calcification on a patient with none.

### TABLE VIII

Stanford vs Our Model (DICE)

|                | Test | Development | Train |
|----------------|------|-------------|-------|
| Stanford Gated Model | 0.739 | 0.813       | 0.914 |
| Our Gated Model     | 0.948 | 0.955       | 0.963 |

To create the model we began by taking the original code
available on github which was used to train the Stanford
Gated Model and changed parameters and data processing to
improve results by 76.8%. The Stanford Model used basic
division of 255 normalization. We changed this by using a
min-max normalization method. Furthermore we increased the
upsampling ratio to 10, meaning each slice that had
calcification would be repeated 10 times, giving the model
more positive data to train on since the model was very biased.
We encountered an error in the calculation of the Agaston
Score which was used to calculate final scores. The pixel size
(mm) was used to find out how much calcification was in the
arteries, and it was a fixed number in the Stanford Model's
code. This was not true as different patients had slightly
different pixel sizes which would affect the final CAC score,
in turn affecting the medication or level of danger (bucket) they are put in.

V. DISCUSSION

As the combined field of healthcare and machine learning
grows in popularity more accurate diagnosis comes as a result,
yet many problems that do not have clear datasets are lacking in
research. Nongated CT scans are a very popular method of
diagnosis for different issues in the medical field. This stays
true for the detection and segmentation of heart disease. While
a lot of research has been done on predicting the CAC score
through gated CTs, not a lot has been done on nongated CT
for CAC scores.

Stanford released a dataset containing both gated and non-
gated data, while gated data seems to be a lot more reliable and
contains more information that would be useful to a
machine learning model. It would be optimal to create a model
that would predict accurate CAC scores on the nongated CTs
versus gated CTs.

Some of the papers released had the objective of creating a
model which could detect calcification and predict the CAC
score from the gated CT scans, such as the cs230 group project
by Stanford.

Possible further research in this topic could be

- Low-cost, efficient, and real time computational platform
  for immediate Agaston Score and bucketing score of level
  of calcification in the arteries of a patient when scan is
  clicked. (Gated & Non-gated)
- System can predict location of calcification very accu-
  rately with a low mean squared error of 62.38 → leads to
targeted treatment plans and improved therapeutic design
before calcification progresses any further to a severe
heart attack
- Addresses calcification on both Gated & Non-gated
  meaning it can also be used as a second hand device
to locate calcification faster and more accurately.

In the future, working on the U-net model specifically
through the training of nongated scans by manually segment-
ing the scans with the help of a radiologist or doctor would
also be quite valuable. Requesting for other private datasets
by medical facilities on nongated scans for more data to train
the model on would produce higher performance.

VI. CONCLUSION

Heart disease and heart attacks affect thousands of people
everyday. To reduce the mortality rate of these diseases we
can detect and locate the severity of the heart problem as
early on as possible. The gold standard for finding the severity
of any heart disease or attack is by locating the amount of
calcification in the arteries of the heart. In the medical field,
this can be done through a specific scan called Gated CTs,
but this is not periodically taken and contradicts the idea of
being able to detect heart issues early. The alternative, more
periodocally taken scan is the nongated CT. Tools like the one
presented in this research can be used by both patients and
radiologists to provide a better diagnostic of the danger of their
situation. Furthermore as medicaid and medicare do not cover
the costs for the search of calcification, tools such as these
prove more valuable. Our unet model was able to perform with
64% bucket accuracy and had 62.38 mean absolute error on
nongated scans while not being trained on a single nongated
scan. To reduce the number of deaths that occur each year
tools like this unet model are useful.

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