Low-Cost System for Automatic Quantification of Coronary Artery Calcification using Artificial Intelligence and Cloud Computing

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***Abstract* — Coronary Artery Disease (CAD) is a major cause of death for men, women and people of all racial groups. In 2018, Egypt had 163,171 deaths from CAD, about 29% of the total deaths that year. According to WHO Egypt is ranked 15 on the world`s rate of death from CAD with 271.9 deaths per 100,000 of population [1]. These numbers indicate the seriousness of the disease that Egypt is facing. Detecting this disease is time dependent and human error prone, Experienced Radiologists examine a patient`s CT and calculate the volume of Calcifications found inside the patient's heart. In this Paper, we propose a framework of Automated Deep learning Algorithms for the Quantification of the Calcification Volume from Low-dose Chest CT. Using two consecutive networks, the first is a Segmentation Network its main purpose is to identify our Region of Interest (ROI) which is the heart, each patient's Specific ROI is then passed to the second network which is the Calcification Quantifier. Both networks Return a Segmented output. The Final output is then processed to roughly quantify the patient's Calcification Volume which will help in his\her Therapy. The Results achieved by the Networks were assessed using the Dice Coefficient metric. Heart Segmentation output reached 90% Score while the Calcification Quantifying Network reached - [ADD RESULTS]-. To reach out to the medical and scientific communities we then added this framework to a well-known Open-Source Application 3D Slicer, which will elaborate its usage and promote the research done in this area.**

***Index Terms*—Coronary Artery Disease, Cardiovascular Diseases, Risk Factors, Whole Heart Segmentation, Calcium Scoring, Neural Networks, Convolutional Neural Networks.**

I. Introduction

Coronary Artery Disease (CAD) is a global leading cause of death. The disease is multifactorial and many predisposing risk factors are responsible for this disease. CAD occurs when the main blood vessels that supply the heart are damaged or injured which leads to shortage of blood supply to different heart regions. Blood shortage inside the heart could result from the Accumulation of Plaques, accumulating over time leads to artery wall swelling which blocks the blood path to the following heart regions. These plaques mostly consist of Calcium, Lipids, Macrophage, Debris or a various amount of Fibrous tissue which can be detected in a computerized tomography (CT) scan by an Experienced Radiologist. There are different types of Plaques that can accumulate inside the arteries, some plaques contain a Calcified Nodule which is easily apparent in Imaging Modalities while there are others that are not calcified but appear as a narrow (stenosed) artery. These Stenosed Arteries contain Soft Plaques that are prone to rupture, such action is responsible for about 70% of acute myocardial infarctions that cause sudden death.

Coronary Heart Disease (CHD) and CAD are interchangeably used terms by Health Professionals, both terms are accompanied by the term Risk Factors which are the traditional indicators of the disease like Age, Gender, Race and Family History [2]. Men are usually at higher risk of CAD while women risk only increasing at menopause. While family history is considered the higher contributor to the CAD Risk Factors, Racial origin is a relevant contributor, African Americans are reported to have higher risks of accumulating CAD Risk factors due higher obesity rates, diabetes and other diseases [3]. Other Risk Factors include Smoking, High Blood Pressures and Cholesterol Levels, Diabetes, Overweight and Obesity and Physical Inactivity. These Risks are arguably controllable which are also the patient's Therapy, Healthy Diet, Stop Smoking, Running etc. Risk Calculators are nowadays a traditional way of calculating a Patient's specific 10-Year Risk of formulating a cardiovascular disease. These Calculators depend on the presence of the previously discussed Risk Factors. Several research results showed that these Factors can be combined in a mathematical equation and give a rough estimation of the patient's specific Risk of getting a CVD or even a severe heart attack in the next 10 years. These Calcified plaques despite not being as dangerous as the Rupture Prone plaques can contribute significantly to the Risk Factors of getting a CVD. CAD Risk Calculators do not include such factor into their calculations and it is still in research so including a tool that facilitates the calculation of the CAC can help with the research in this field.

While there are several Assessments and tests that help identify CAD, Imaging comes as the most reliable assessment procedure. Different Imaging Modalities exist with different features and cost. Contrast-Enhanced Coronary CT Angiography (CCTA) is one of the recently widely used modalities that uses ECG-Gating/Triggering to Capture the Heart accurately and at the appropriate timing. Advancing in Scan Time and Image Resolution CCTA comes with the Disadvantage of Radiation Dosage Exposure which may be following the Standard Health Regulations but is still Costly.

Cardiac Magnetic Resonance (CMR) is another Non-Invasive Imaging tool widely used while it also produces high resolution images, many patients dislike the procedure as it includes entering a closed casket-like machine for long times until scanning is finished, the Magnetic Resonance Imaging (MRI) machine is also intolerant to magnetic objects pacemakers, defibrillators and implanted pumps. While the faster modality is CT it needs high doses of radiation to produce a high-Resolution Image, decreasing this dosage could help in reducing the scan cost which then help research and encourage patients to go through the routine check-ups that helps in detecting CAD.

A Patient that experiences CAD Symptoms is advised to first do a CT scan which is presented to his/her personal Physiologist. This scan may contain sufficient evidence of the patient's risk of CAD. Blocked Arteries are presented in the scan as white dots that appear inside the heart region, due to the presence of Plaques which contain a decent amount of calcium that appears white (Bone-like Structure). A Radiologist examination of the scan is to Annotate (Segment) these structures across the whole heart region then estimating the total volume of these white voxels. The resulting amount is a CAD indicator which is relevant enough for the Patient's Physiologist to recommend a Patient's specific therapy according to his/her case.

This process of annotating each patient scan is time consuming and highly costly, estimated about 6-10 hours. Cost problems come in the way of doing Expanded Research that helps explore the disease and produce publicly available data. Low Dose CT scan can be a sufficient solution to the problem, keeping the fast-scanning times, Patient tolerance and cost but comes at a price of low-resolution results which can then be solved using computational powers in which comes our proposed systems. The current goal is to quantify each patient's CAC Volume as it is a strong indicator of his/her risk of getting a CAD and adding a future goal to identify stenotic arteries as Soft Plaques are another dangerous kind of Plaques.

II. LITRATURE REVIEW

The Calculation of the Calcified Plaques volumes is a one of many research subjects that is widely discussed that is why it is an important topic. Several Challenges are presented by organizations to solve this particular task like the orCA Score Grand Challenge. There is also the National Lung Screening Trial [4] which is a more generalized examination done on a huge number of patients in the US. The Trial had over 50,000 patients, all with heavy smoking habits. The goal was to relate Smoking with Lung Cancer but it was also found that Smoking is related to the presence of CVD and patients that adopt a heavy smoking lifestyle are at risk of CVD as much as Lung Cancer. The Data was used by Nikolas et.al. [5] proposed method to detect and quantify Calcified Plaques volume using Fully Convolutional Neural Networks. The Proposed method consisted of two Convolutional Neural Networks. The First Network in Fig. 1 identified and labelled candidate calcifications based on their location inside the patient's specific ROI. Using 3 parallel subnetworks for each view inside the input volume which is called 2.5D instead of using a 3-Dimensional Convolutional Neural Network which as he stated was a superior method to that of the 3D Convolutions. The Network also added Dilation rates into the Convolution which is done to increase the receptive field of the model. This typically increases the network's attention to detail inside the image since this network's main task is to extract all candidate calcified plaques.

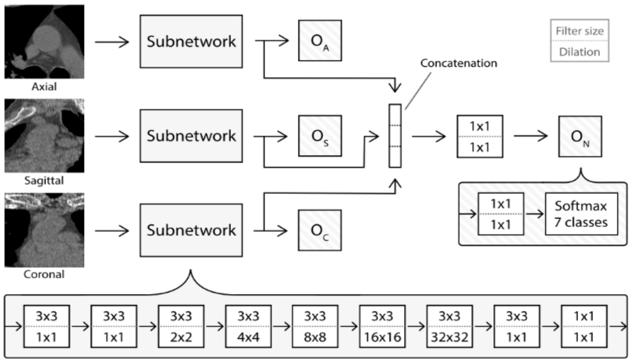

Fig. 1 The First Network Proposed by Nikolas et.al.

The Second Network in Fig. 2 used by the Author is also a fully convolutional network without the dilation rates. Its main task is to reject the False Candidates detected by the first network by simply taking the output from the first and retraining on the data which then helps the model extract false positives from true positives. The overall proposed network's performance is estimated by the author to achieve about 0.89 F1 Score (Dice Coefficient) for the Coronary artery calcifications.

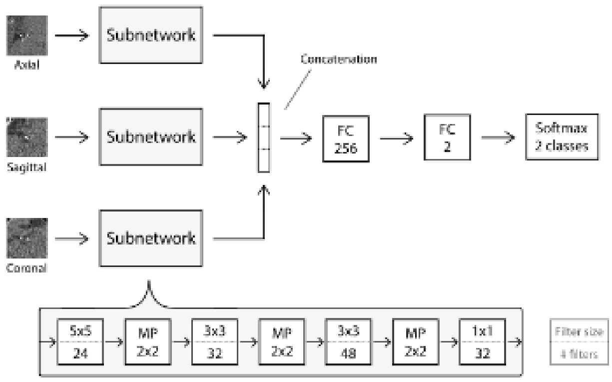

Fig 2. The Second Network

Although there exist now a huge amount of Machine Learning and Deep Learning approaches to solve this particular task, Computer Vision possesses a variety of techniques used before the invasion of Deep learning that had a decent performance. The orCaScore Grand challenge had submissions with such techniques varying from thresholding and using Hough transforms to detect the ROI to Simple Machine Learning algorithms to identify True Calcification candidates. Jelmer et. al. [6] presented an evaluation of the methods submitted at the Grand Challenge. Five methods have been submitted by different institutes and using different techniques, however they all both share the same Threshold at which they define their candidate CAC. The Thresholding technique is used to extract a candidate Plaque while other structures could also appear like bone the method depends mainly on the ROI identified by the authors as other calcifications can appear like aortic calcifications which are not the target of this task.

One of the Recent published researches was presented by Zeleznik et. al. [7] where they proposed an Automatic Deep Convolutional System that Identified a patients' specific ROI and segmented the candidate Calcifications manifested in each patient. Their method achieved about 0.9±0.05 Dice Score in the Whole Heart Segmentation Task. While their Calcification quantification achieved a Kappa of 0.76. The Networks proposed in their article consisted of 3 Steps, The First is a Localization Step where the Network output a rough location of the patient's heart according to the input scan, The Second is trained on a cropped volume according to the location from the first network while the Last step is the Calcium Quantification network that segment the candidate calcifications. They trained their System on Data obtained from multiple sources like the NLST and PROMISE Data bases.

III. Materials & Methods

A. Data

1) Multi-Modality Whole Heart Segmentation Challenge (MMWHS)

In order to create our proposed system, we need the presence of Reliable, annotated and large Data. The First System' task is to Segment and Extract the Patients' Specific Region of Interest (ROI) which is the Heart and it's branching Arteries. The Multi-Modality Whole Heart Segmentation is a challenge [8] that presents Fully Segmented Heart in both CT and MRI Modalities with 120 Scans (60 CT + 60 MRI). The CT scans were accompanied by a CT Angiography (CTA) Scans which are higher in resolution. Both CT and CTA came from 2 standard 64-Slice CT Scanners (Philips Medical Systems, Netherlands).

The Scans cover the whole heart from upper abdomen to Aortic Arch with 0.7mm x 0.7mm Resolution and an Average Slice Thickness of 1.6 mm. The Data Quality varied as it was captured from local environments which then helped increase the System's robustness and Validation. The Data Annotation was done by Clinicians or by students majoring in Biomedical Engineering or by Medical Physicists who are familiar with the whole heart anatomy. The resulting Annotations were then validated by Senior Researchers Specialized in Cardiac Imaging. Each Scan was estimated to take from 6 to 10 hours to completely annotate the whole heart.

2) orCaScore Grand Challenge Data

The Grand Challenge Platform Provides a Framework for the Identification of the Coronary Calcifications [9]. The framework contains data for both Non-Contrast and Contrast-Enhanced CT Images collected from 4 different Academic Hospitals, 4 different CT Vendors. The Dataset consists of 72 Records for 18 Unique Patients, 9 Females and 9 Males. The Records were Distributed among 4 Cardiovascular Disease Categories (CVD). The Scanning was done with a Multidetector row CT with ECG-Triggering on Diastolic Rest with, 70% for GE & Siemens, 75% for Toshiba and 78% for Philips. Further Specifications for each Vendor were described in Table 1.

Data Labelling and Ground Truth were annotated by 2 Experts in the field, the first is a 12 Year Experienced Radiologist and the Second is a 5 Year Experienced Research Physician. In further joint sessions the ground truth for the data was set by consensus and both experts' results were saved and evaluated.

Both Data sets included different labelling including the location of the segmentation task at hand. For the heart, the location of each structure is labelled inside the heart and for the Calcified plaques the location of each plaque inside the different coronary arteries. As we intend to only produce a rough location of the Heart as a specific patient's ROI and the Calcified plaques volume, we normalized all segmented masks to only contain two classes, The background presented as a 0 and 1 for the targeted task either the heart or a calcified plaque.

Table 1 Describes the Vendor Setting Selected in the Grand Challenge Framework

SETTING	CSCT	CCTA
TUBE VOLTAGE KVP	120	120 or 100
RESOLUTION (MM^2)	0.4x0.4 - 0.5x0.5	0.4x0.4 - 0.5x0.5
SECTION THICKNESS	2.5 GE 3(Philips, Siemens, Toshiba)	0.625/0.625 mm (GE) 0.9/0.45 mm (Philips) 0.6/0.4 mm (Siemens) 0.5/0.25 mm (Toshiba)
KERNEL	Standard (GE) XCA (Philips) B35f(Siemens) FC12(Toshiba)	Standard (GE) XCA (Philips) B30f (Siemens) FC03 (Toshiba).

B. Methods

1) Dice Coefficient

We used Dice Coefficient as a metric to assess our model's performance. The Dice Coefficient is a Generalization of the Intersection over Union metric (IOU). The IOU is used to identify the model's performance in segmentation tasks; it is an indicator of how the model is able to capture the structure needed to be segmented. As the Fig. 3 states the more the overlap between both the predicted segmentation and the Ground Truth increases the higher the IOU value gets.

$$IOU = \frac{|Prediction\ x\ Ground\ Truth|}{Prediction + Ground\ Truth} = \frac{TP}{TP + FP + FN}$$

On the Other hand, the Dice Coefficient is a more generalized metric the difference is that the Dice Coefficient can somewhat measure the average performance of the model in a single inference while the IOU measures the worst-case performance. The Dice Coefficient also called the Overlap-index is the most used metric to assess Segmentation tasks and is heavily used in medical imaging techniques. The loss function is simply Negative the Dice Coefficient value using the defined Optimizer to decrease the Model's loss and Increase the Model's performance.

$$DICE = \frac{2\ |Prediction\ x\ Ground\ Truth|}{|Ground\ Truth| + |Prediction|} = \frac{2\ TP}{2\ TP + FP + FN}$$

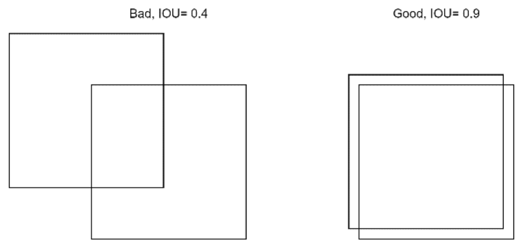

Figure 3 A Presentation of the true meaning of Intersection over Union Metric and how it can present Segmentation Performance.

2) U-Net Archeticture

Deep Learning Techniques have seen an enormous rise in performance compared to the traditional Computer Vision Techniques. The Computational Intelligence Community has provided a lot of Outperforming Techniques in Visual Tasks. The U-net Architecture is one of the Networks created Specifically for the Medical Images Segmentation Task. Olaf et. al. [10] Intended this Architecture to excel at Localization Tasks in Medical Images with low computational cost and decent Performance. The Network consists of two consecutive paths, The First path consists of consecutive down sampling steps and the Second consists of consecutive up sampling. The Network is a Fully Convolutional Network each step is followed by a number of Convolutions with a number of Filters. To improve the Network's ability to assess higher resolution images each down sampling step output is concatenated with the opposite up sampling output to compensate for the information loss from the down sampling step. This technique helped the Author win the EM Segmentation Challenge in 2012.

There are a huge number of deployed, working and highly performing techniques. We choose the U-Net Model approach due to its ease of Implementation, Robustness against different data and the Ability to learn how each modelling parameter affects the resulting segmentation. Our Proposed System uses this architecture with different parameters than the originally used in the 2015 Paper.

We also dived through different techniques but due to the difference in Modalities used in the publicly available Datasets we came short of each research's findings. For Example, the Harmonic Dense Net is a robust architecture used on the KVASIR-SEG Dataset [11], The network proved its performance exceeding other networks used on the same dataset with about 0.9 Mean Dice Score. However, as we progress in our research the network reached about 0.75 $\pm$0.1 on only the short axis 2D Images from the Heart Volume.

In Fig. 4 the U-Net is presented in Two paths, the Down sampling path uses a Max Pooling function to decrease each step's input to the next step, it is conventionally used with a (2, 2) Kernel or a (2, 2, 2) for 3D Inputs. The Pooling Layer's task is to divide the Input into overlapping windows with the given kernel size and compress the output to only the maximum value presented inside this window. Before each down sampling step, the author added 2 convolutions with Same Padding to preserve the input shape, it is conventionally to use a filter number that is a power of 2 which is a Convolution tolerant number and it is a convention followed in all computer vision aspect it is also a convention to use odd sizes for the kernel filter size of the Convolution, example (3, 3) or (5, 5), the Author here used a (3, 3) conventional kernel size. In the Up-sampling path, the author used a Bilinear Interpolation Up sampling function. The performance of the Up Sampling Function depends on the interpolation technique it uses as there are a number of different techniques used in interpolation the often-used ones are Nearest Neighbor interpolation and Bilinear Interpolation.

Inspired by the Article by Zeleznik Et. Al [7], we used the designed network in Fig. 5 The Architecture contains 4 down sampling steps with 2 consecutive Convolutions. All convolutions used a RelU Activation function with filters that are doubled at each convolution. The Training was done on a Single GPU NVIDIA GTX 1080 TI with 11 GB Memory, Python 3.6.7, CUDA 11.4 and libcudnn 8.2. Model Training continued for about 100 epochs before reaching a plateau where the Loss did not converge any more. The Data was passed to the model after a series of Pre-Processing Functions, Rescaling the data to the 0-1 Range, Applying Resizing Kernels to fit the Input Scan Volumes into the Model we resampled each volume to (112, 112, 112) and Applied Different Augmentation Techniques, Random Axis Flipping (First and Second Axes), Random Gamma Corrections and Random Rotations in the Axial Direction of ±10 Degrees. The Loss Function used was Dice Loss and Optimization done by Adam Optimizer with 0.0001 learning, we applied a Decay callback on the Learning rate to decrease the learning rate on plateau. Our U-Net implementation was done in TensorFlow 2.5 using the Keras API.

Inspired by the techniques submitted at the orCaScore Challenge we used a Thresholding technique to identify candidate calcifications. Large volumes that pass the threshold like bone structure are removed first then we use our predicted ROI to only quantify calcifications manifested inside the Coronary Arteries. However, as we discussed in the literature review this method has a limitation that prevents it from excelling performance as the resulting calcified volumes include the Aortic Calcifications which is for now a limitation that we are working on.

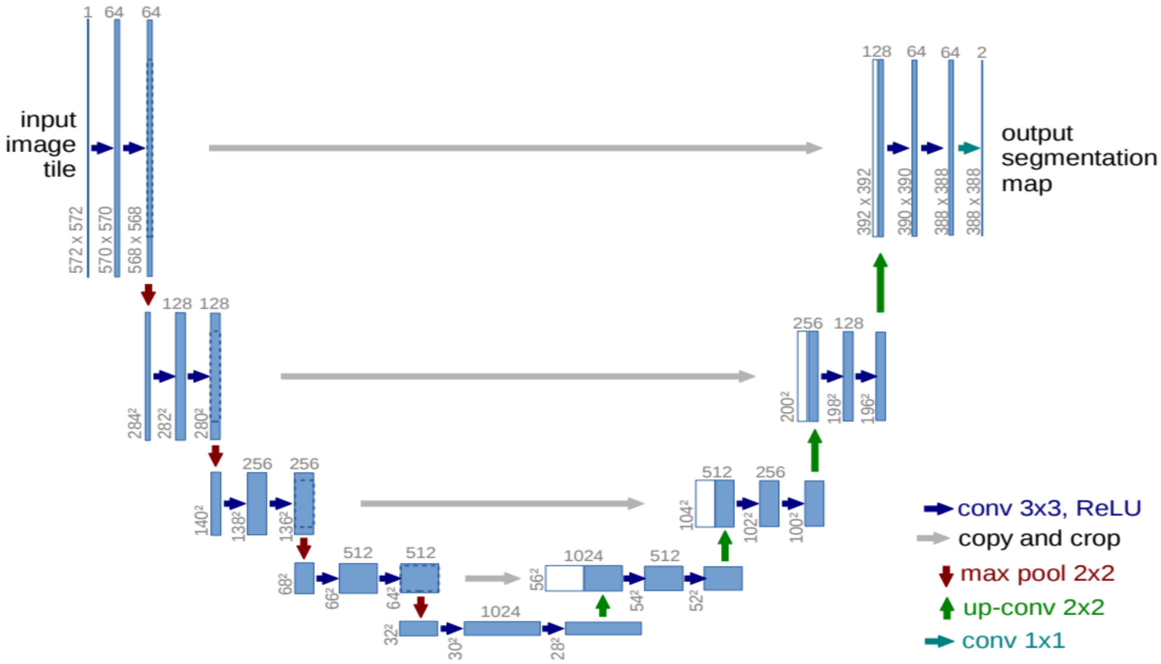

Figure 4 The U-Net Architecture Design presented by the original Paper Authors

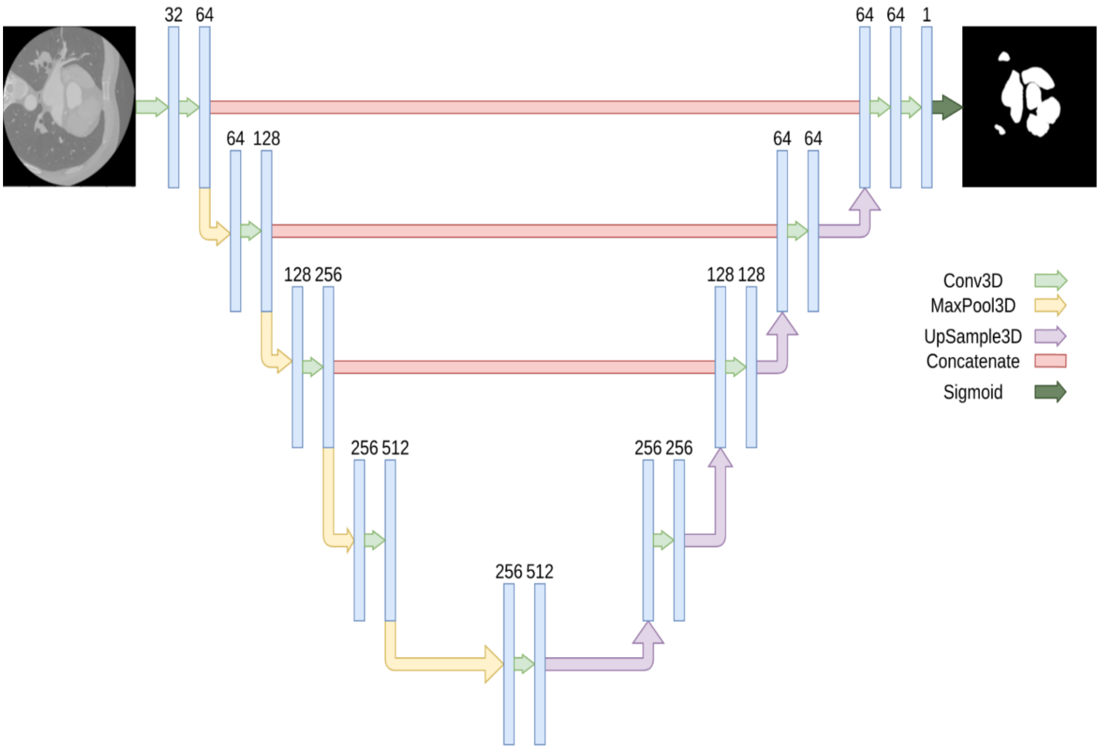

Figure 5 The Unit Architecture Inspired the Deep CAC Article and Used in our Implementation

3) 3D Slicer Plugin

Our main goal was to provide a tool, presented in Fig. 6, that could automatically quantify calcium volume of the calcified plaques in the Coronary Artery. This volume, also known as calcium score, is one of the risk factors used to predict the likelihood of Coronary Artery Disease Events occurring in the next few years. This process is currently being done manually by Radiologists, this takes a long time, and the results are subjective. This is what motivated us to make this extension, as a way to help make this process better and more streamlined as there is currently no widespread tool that helps on this front.

We have two main modes in our module Fig. 7, Local Mode where the data is processed locally on the user's machine, note that for optimal performance, a system capable of running TensorFlow Models is needed, A CUDA-Capable GPU will increase performance drastically, TensorFlow and other required packages needs to be installed inside Slicer's Packaged Python, A check will be done during first operation in this mode and all the required packages will be automatically installed. Online Mode where the data is processed online, the volume is sent to a given URL which will process the data and send it back, an example server is included in this repo together with a requirements file.

Selecting the Cropping Checkbox enables cropping, it uses the results of a Deep Learning model built using TensorFlow to segment the heart, determining its location, then we create a bounding box around the ROI (The Heart) predicted by the model and crop out everything outside it. The Partial Segmentation Check Box enables the Partial Segmentation mode, in this mode we select the three middle slices from the Axial, Sagittal & Coronal views and use them to get the bounding box's coordinates used in cropping, while it's not as accurate or useful as segmenting the whole volume, it's role shines as a pre-processing step, this rough cropping could be done before segmenting the whole volume to increase its quality, or decrease the volume's size which is useful in cases of using the online mode in a low or limited internet bandwidth setting. Create a Segmentation node from the results of the full heart segmentation, enabling this disables the partial segmentation option, this segmentation is shown over the input heart CT image and shows the location of the heart, it could also be converted into a closed surface representation of the heart.

This option is required to find calcifications. Enabling the “Visualize the Heart as A Closed Surface” creates a closed surface representation of the heart's segmentation, this creates a 3D view of the heart which could have numerous benefits, this option requires the full volume segmentation and the creation of a segmentation node. Our module uses one of two methods to quantify the Calcifications found inside the patient’s heart, by default uses Image Processing techniques to determine the calcification then calculate their total volume which Require full heart segmentation. The image processing option uses image thresholding (>130-160) to find all locations containing calcium in the volume and saving it in a Calcifications volume, we then use it to get two different volumes, Calcifications in the heart's segmentation area, this is done by masking the calcifications using the heart segmentation prediction, so only calcification inside our predicted heart are detected. Ignoring calcifications in the calcifications volume which are located near known bone masses. By adding these two, we create a new volume which accurately locates all calcifications.

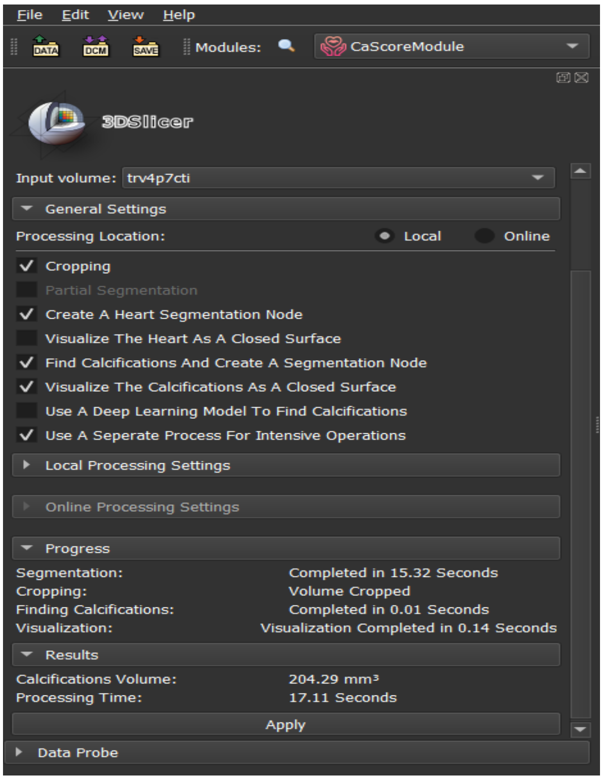

Figure 6 3D Slicer Graphical User Inter face and displayed Commands

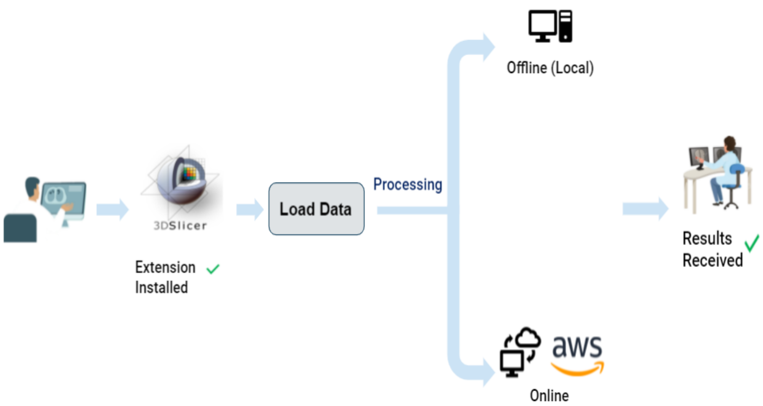

Figure 7 Diagram presenting the Extension’s work from the Loading of data into slices to the return of the results to the user with all the possible routes that a user can use either Online Processing or Offline.

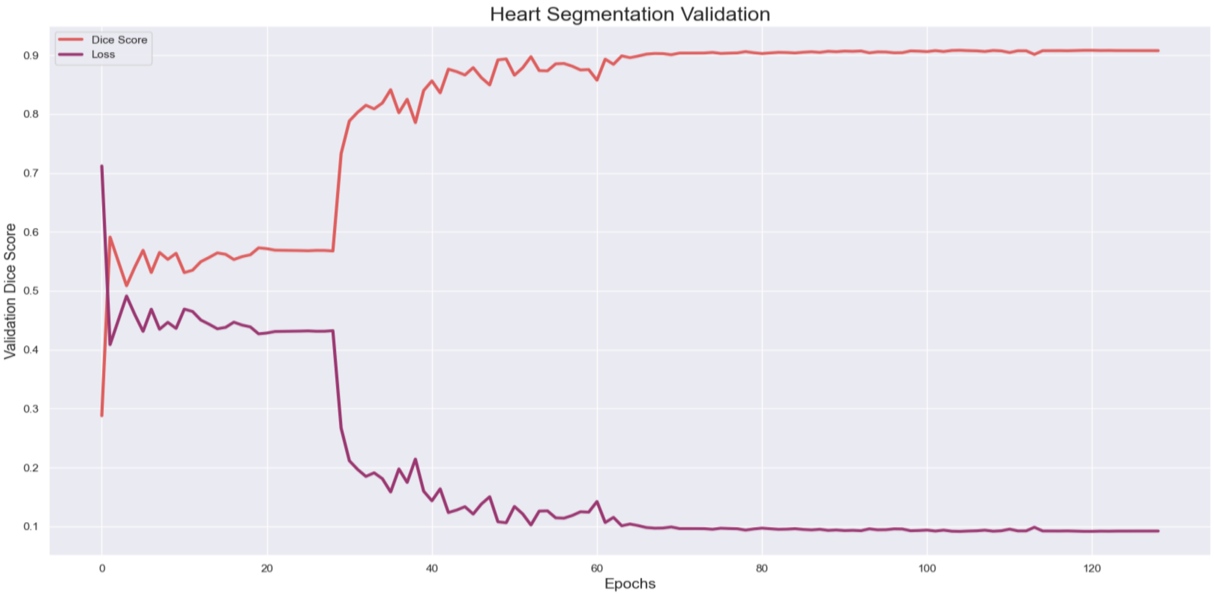

Figure 8 Heart Segmentation & Localization Training (Upper) and Validation (Lower) progress and conversion to 90% Dice Score

IV. Results

Training and Validation results were recorded for both the Heart and Calcification Models with the Performance metric being the Dice Coefficient and the Loss Function Dice Loss. Heart Segmentation Network Achieved a Dice score of 0.9 in Validation on a different set of Data than those the model trained on. Training and Validation history is plotted in Fig. 8. Despite training the Calcification Network for about 700 epochs the model never converged and its results remained underwhelming. While the Thresholding technique with its limitations achieved a 615 mm^3 Root Mean Square Error (RMSE). 3D Slicer's Plugin Extension is deployed and running on an AWS Amazon Server. The Plugin is still under development so it is only available on our GitHub Repository but can be easily loaded into slicer and easily run. From the Validation data we loaded a Patient's Scan and Run our whole system with the results presented in the Fig. 9.

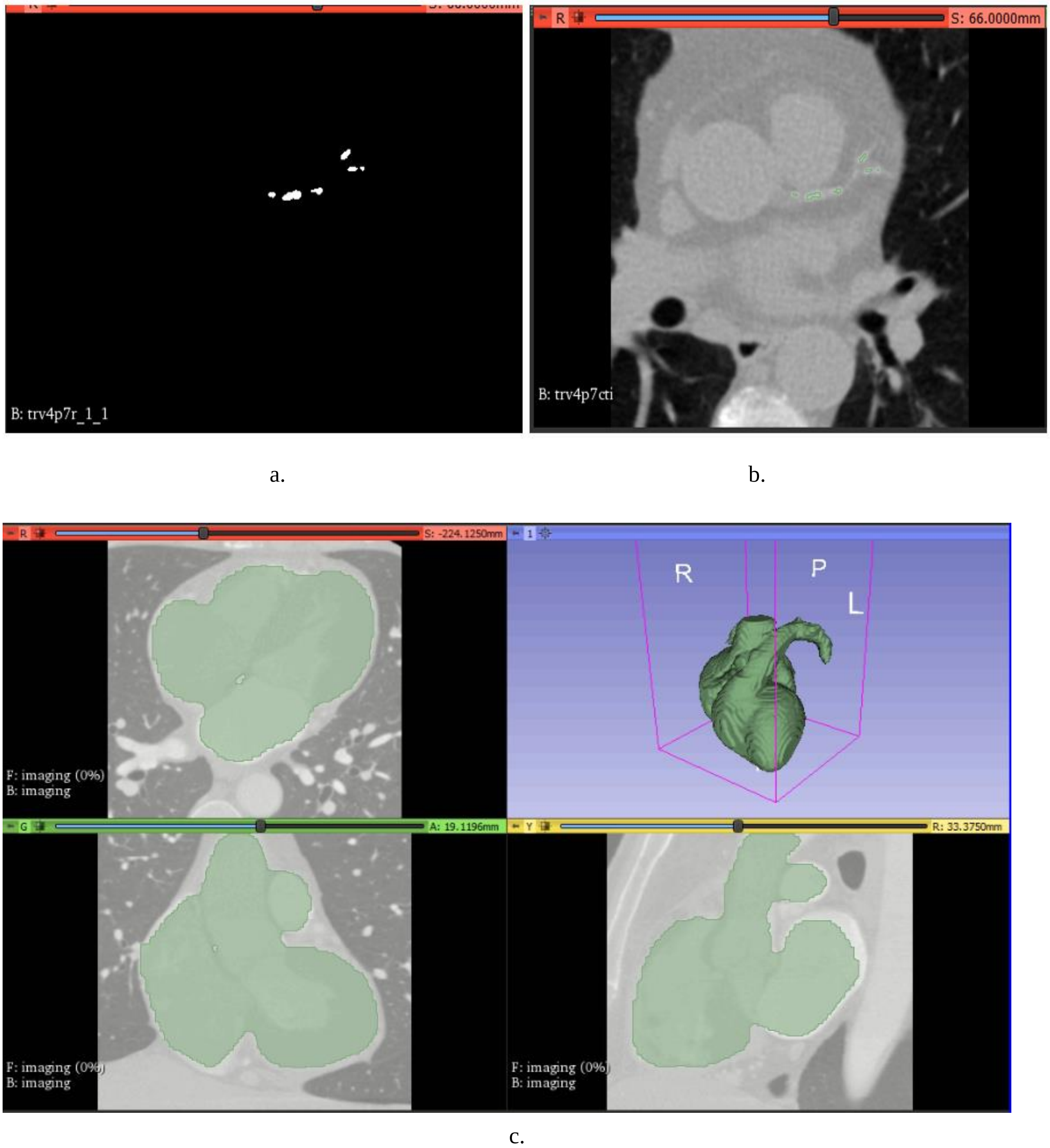

Figure 9 Results Captured from Live Demo inside our Developed Extension. A&B) Comparing the Resulted Calcification Segmentation and the Ground Truth from the orCaScore Grand Challenge Data, C) The Heart Segmentation and Localization Output from the First U-Net Model.

V. DISCUSSION

CVD Traditional Risk Factor Calculators do not include CAC Volume also known as the Agatston Score in their estimation of the patient's risk. However recent discoveries confirmed the strength of the CAC Volume as an indicator of CVD. Tools are not yet presented widely to estimate or quantify this metric but several research papers published solving this task, similar to the ones compared in the Literature Review section. Relevance of the production of such tools is to provide reliable source of assessment and not prone to subjective error or human errors, Fast estimation of the calcified plaques and score which is a time-consuming process to be estimated manually by a radiologist which also includes the high pay of an experienced radiologist.

Estimation of the Calcified plaques or other types of plaques needs an experienced radiologist which is still prone to error and needs a consensus with other experienced radiologists to define a Ground Truth annotation for large or wide Research Trials. The main Risk factor here is the presence of an accumulating Plaque with its various types. Plaques can exist in 3 forms, The first which is the Soft Plaque, this type is prone to Rupture which is alone a dangerous action as the resulting materials from the rupture of this kind of plaques can lead to sudden complete blocking of the arteries due to the interaction of the blood with these materials which produce clots that might endanger the patient's life. These plaques appear as a narrowing inside the artery which can be clear in an Angiography CT scan, using a contrast material. Other types of Plaques can contain Calcifications which is our current target, quantifying the number of calcifications present in a patient's heart can be an indicator of the risk he is in of inhabiting a CVD.

Our search started with U-Net implementation from its original paper. The flexibility of the implementation was our main goal at this process as we needed to search a number of hyper-parameters which with an ill-defined implementation this iterative process of training and modifying parameters and retraining again will be tiring. We then tested with different parameters like the number of down sampling steps and the number of consecutive convolutions and their filters. The main performance metric changer is the use of Bi-Linear Interpolation Function. We experimented with a method called Transposed Convolution, this method is adopted by one of the papers discussed. Transposed Convolution or De-Convolution is a learnable function and does not use any interpolation function to re-scale it/s input to higher resolutions. The results from using these methods were not promising so we switched to another discussed method which is the Harmonic Dense Net (HarDNet). The HarDNet was intended for the segmentation of Polyps inside the colon and achieved robust results. Using transfer learning to transfer the model's learned experience in its targeted task to help us with our needed goal. HarDNet achieved about 0.75 Dice Score in the short axis only. Training the HarDNet on the whole heart volume resulted in a lower Dice Scores which led us to another switch in the used Architecture.

Recent Studies by Zeleznik et. al. inspired us to re-train our implemented U-Net Model with the help of the parameters found useful in their methods. Bi-Linear Up Sampling techniques and their model's parameters from the Learning Rate of Adam Optimizer to the number of Down sampling steps helped us achieve our results in the Heart Segmentation Task. Similar to their work our Heart Segmentation model reached about 0.9 Dice Score against the Multi-Modality Whole Heart Segmentation. Opposite to their work we only needed one step to Fully Segment the Whole Heart this may be a result of different data sources as their work used a huge number of patients and high-resolution scans covering each patient's whole abdomen and this was present in our test on their data where the heart was segmented correctly but with more misclassified structures.

Moving on to the Calcifications Quantification task where we tried Zeleznik et. al. approach using the same U-Net Architecture with different down sampling steps and training on the Cropped Heart Region divided into several Overlapping smaller cubes, the results did not satisfy our defined goal which can be a problem of the presence of small number of patients or the fair imbalance presented in the Data as the Calcified Plaques represent a small volume of the total volume of the Data. Following a more traditional approach to the problem. Image processing offers a wide range of techniques used to identify these Calcified Plaques. Our Applied Technique used a Threshold of 130 HU inspired by orCaScore Submission's approach, removing resulting bone structures and applying our identified ROI in the first model to accurately achieve our defined goal. Parsing the orCaScore data and checking with the ground truth our approach seemed enough to deploy our Plugin in Beta Phase while working on improving our last step. Our approach has a limitation in which we cannot sort out the calcifications present in the Aorta which is not our goal.

The Plugin uses Separate Processes for Intensive Operations done on the images. This option delegates long-running operation to a separate process so that it doesn't block 3D Slicer's UI. This is a problem that plagues parts of 3D Slicer as it mainly works in a single-thread so any long-running or CPU intensive operations completely locks out the user from using the GUI. We choose to use a separate process instead of a second thread for a couple of reasons which are using a different process for CPU-Intensive operations is generally preferred as it is faster than using threads, threads are better suited for I/O operations or any operation that simply involves waiting, since the main operation that we delegate is model prediction which could utilize the CPU heavily, running it in a separate process seemed more practical. Due to the way 3D Slicer is built, and the fact that it runs on a pre-packaged python version and relies on it heavily to complete various operations (Even though 3D slicer is made using C++), threads are incompatible with it to a certain degree, to be able to use threads certain actions need to be made which could destabilize the application making it more error prone and prevent the usage of some functionalities temporarily, this was a point against using threads even though it's generally easier to use them inside Qt.

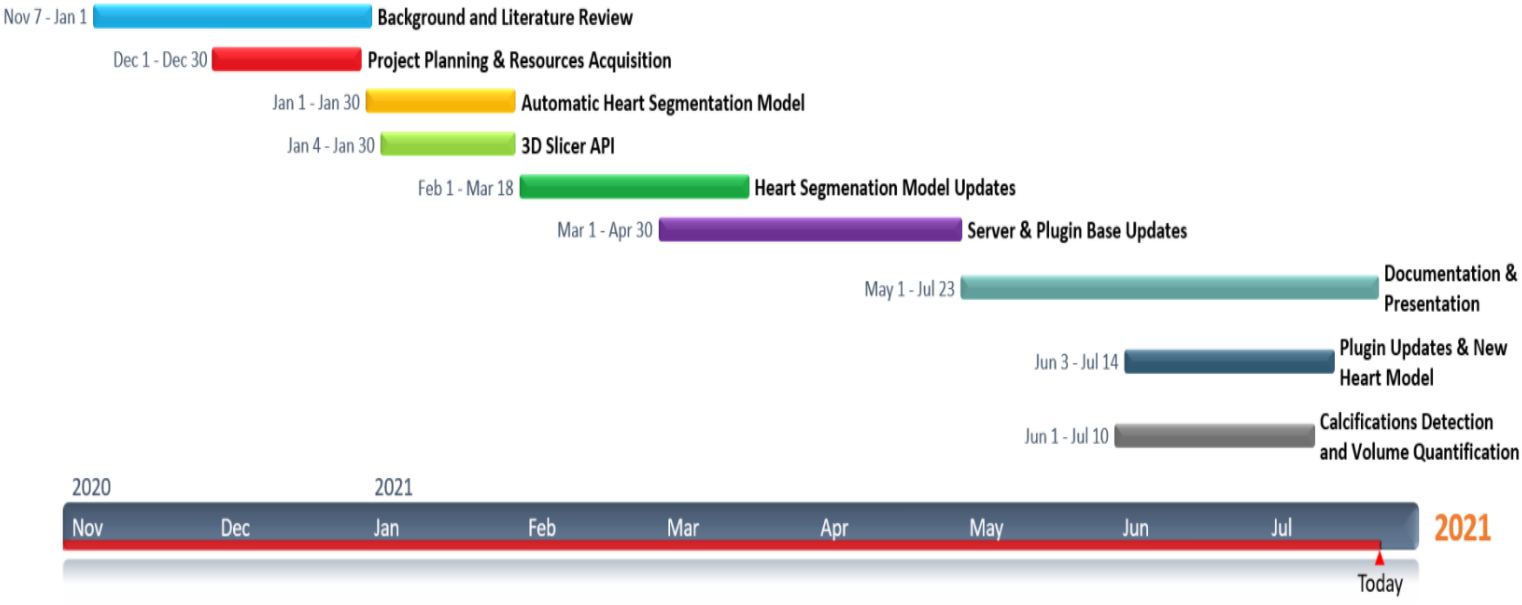

Figure 10 Gantt Chart of our Progress in the Project

VI. Conclusion

Our Developed solution certainly have its limitations but it is a presentation for our imagination of a tool that accelerates the process of Calcium Quantification for the importance of having such tools that helps and reduce the time needed to produce such results. The Processing Time range from 10 to 15 seconds the first time a user uploads a Scan while it ranges from 3 to 5 seconds the rest of the times.

This Project is one step of a whole CVD Identification Suite in which we do not only quantify Calcified Plaques but also identify Stenotic Arteries and extract its centerline. In order to overcome our limitation we need to continue our research in the methods specialized in identifying Calcified Plaques, another theoretical solution is to manually segment whole heart data including a precise annotation of the Coronary Arteries, define another model that could segment this annotation and use the difference between our defined Heart Segmentation model and the new state to extract only the Coronary Artery tree which then we can use the thresholding method to extract it's Calcified Plaques.

Another proposed idea is to provide a Web-based Solution for the entire scientific community and interested users where our provided tool can be used publicly outside slicer.

VII. References

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