Using Machine Learning to Analyze Image-Based Volume Characteristics of Left Atrial Volumes in Atrial Fibrillation Patients

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Abstract:

Detecting atrial fibrillation (AF) using artificial intelligence models is much more efficient than current clinical management methods and can reduce financial burdens on the healthcare industry. The purpose of this study was to train an AI model to detect whether a given sample of left atria (LA) showed signs of AF and the difference between LA volumes of people with and without AF. Using LA image datasets from the Cardiac Atlas Project and MSD Cardiac Dataset, I was able to analyze the images using ITK Snap, load them onto a Python console and use those images to train the AI segmentation model. The implementation of a convolutional neural network was essential in training the model, as it allowed the model to break down visual aspects of the LA and distinguish between AF and Non-AF LAs. The main characteristic used to determine whether a given LA had AF was its volume. After calculating the volume of the LA of both AF and non-AF patients, as well as conducting a significance test, I was able to conclude that the larger the volume of the LA was, the more likely the patient was to be diagnosed with AF. The average volume of LAs in patients without AF was 21839.77 mm³, while the average LA volumes in patients diagnosed with AF was 55649.42 mm³. The significance test showed that there is a significant difference between these two averages. Taken together, these results show that analyzing the volume of the LA is a very effective way of determining whether a patient is diagnosed with AF.

Introduction:

Atrial fibrillation (AF) is characterized by the upper left atria beating out of sync with the rest of the heart, producing an irregular, rapid heartbeat.[1] It is the result of many different electrical impulses of the heart rapidly firing simultaneously. It is the most common type of arrhythmia. There are many types of AF: paroxysmal AF, which generally lasts less than a week and disappears on its own; persistent AF, which lasts for more than a week and requires special treatment to slow the heart rate down; Long-term persistent AF, which lasts for over a year and is very difficult to cure; and permanent AF, in which the upper atria shows signs of unresponsiveness to treatment options. It is usually diagnosed by analyzing the heartbeat, such as by using an electrocardiogram (EKG/ECG), blood tests to analyze potassium and thyroid hormone levels, and MRIs to analyze the heart structure (particularly the LA). Common symptoms include chest pain, dizziness, shortness of breath, and palpitations. It is more common among the older population, as the efficiency of the cardiac conduction system decreases over time. High blood pressure, obesity, genetics, coronary artery disease, and sleep apnea are among other risk factors for AF. If not taken care of immediately, AF can lead to more serious complications such as a stroke or heart failure [2]. Blood flow may slow down, which causes tight blood flow in the LA that eventually forms into a clot. Once the clot breaks loose, it travels to the brain and blocks a blood vessel, stopping the flow of oxygen, resulting in a stroke. Additionally, the increased heart rate causes the myocardium to become less efficient and eventually wear out, leading to heart failure. Treatment options include medications such as Digoxin and Carvedilol, blood thinners like Warfarin, electrical cardioversion which resets the heartbeat, left atrial appendage closure, and often surgery. There are many ways to prevent this condition, including regular exercise, maintaining a healthy diet, and staying away from drugs and alcohol [3].

Imaging is a useful tool to help diagnose AF. Imaging provides all the necessary information in determining whether a patient can be diagnosed with AF and is an efficient alternative to electrical impulse analysis. Segmentation of the LA helps in quantifying the volume of the LA of the heart. Volume of the LA has been associated with onset of AF in clinical literature. [4]. This method can help in better management of the disease. Depending on how large the LA has become, appropriate treatment options can be assigned to patients. Those with severe AF could be given catheter ablation, a procedure in which tubes are used to fix specific parts of the heart. Additionally, pacemakers could be assigned to increase the heart rate. Paroxysmal AF can be treated with medicine and cardioversion [3]. Traditional ways of detecting AF focus on the heartbeat, which is important as the main characteristic of AF is an irregular heartbeat. However, with imaging, the severity of the disease can be diagnosed as well as other important structural features.

In this study, I perform segmentation of LA of AF and non-AF patients using artificial intelligence (AI) and quantify their LA volumes. I then compare the LA volumes in the AF and non-AF groups and perform significance testing.

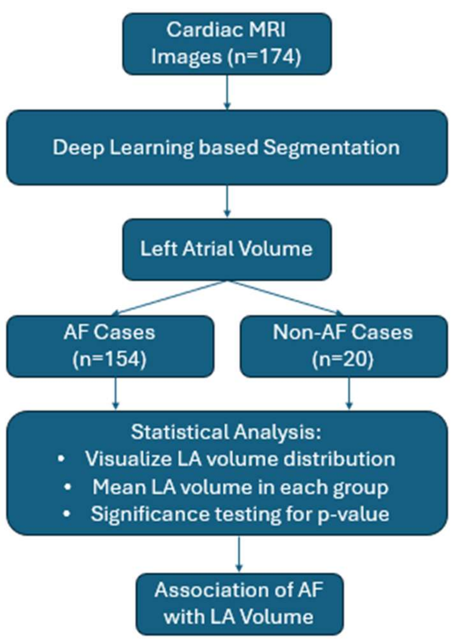

Figure 1: Flowchart of the study design

Methodology: This study required the acquisition of two separate datasets: MRIs of patients' hearts diagnosed with AF and those without AF. I was able to find the data set of patients diagnosed with AF through the Cardiac Atlas Project's 2018 Atrial Segmentation Data.[5] The MRIs of patients without AF was found on a dataset from GitHub called Awesome Medical Dataset [6]. Both datasets contained MRIs of each patient's heart as well as a separate segmentation of the LA. Additionally, each dataset contained a training and testing set to train the AI model with.

In order to detect whether a patient was diagnosed with AF, segmentation of the LA of each heart was required. The utilization of ITK Snap was key to the segmentation of each heart. First, I loaded a single image into the software. I then located the middle slice of that image (which was the 44th slice), as that slice would be essential in identifying the general shape and structure of the LA compared to the rest of the heart. After doing this for 1 image, I then loaded this image onto a Python console using the nrrd, and matplotlib.py classes. The nrrd class was used to read the AF images as the images were all NRRD type. Matplotlib was used to plot and display the appropriate portion of the image. The next step was to load the same slice for all 100 images in the training dataset. Loading these images offered a clear side-by-side comparison of what a typical heart diagnosed with AF looks like. These same steps were then replicated for the 20 non-AF cases. Visually analyzing the hearts of patients diagnosed with and without AF gave a clear indication of which section of the heart was affected the most by this disorder. The main difference was that the LA of the AF patients was clearly enlarged in comparison to the non-AF patients, and some AF cases even showed signs of inflammation in or around the LA.

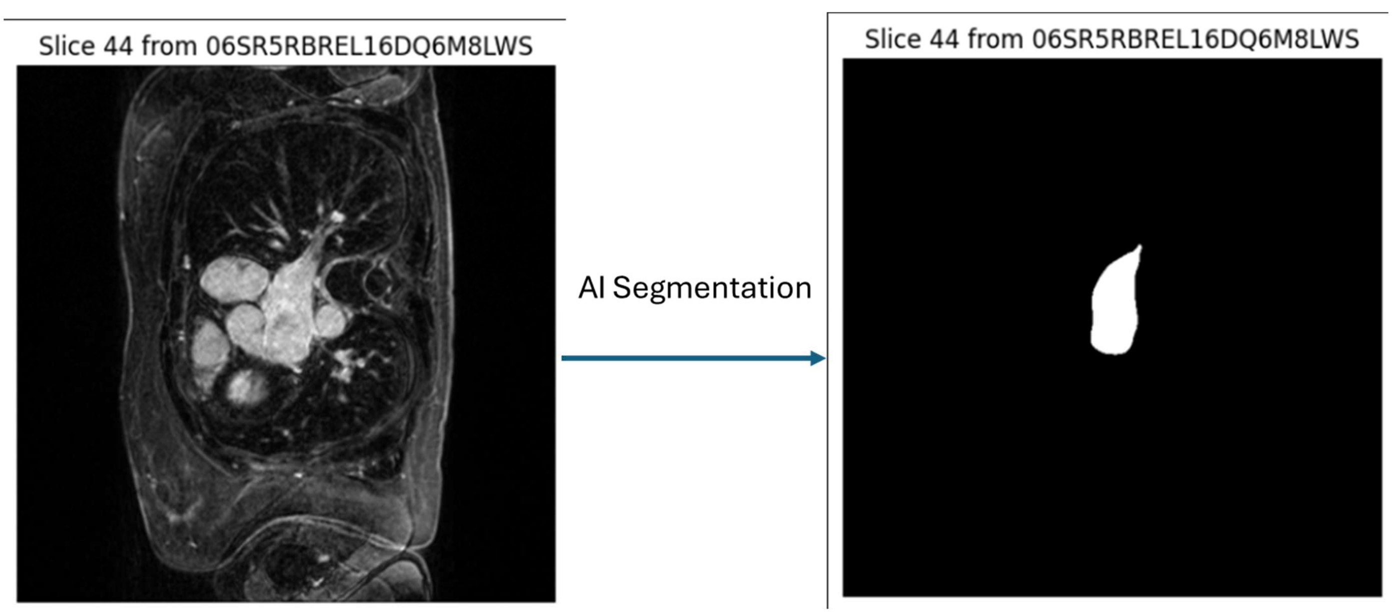

Figure 2: Example segmentation for one LA

To determine whether the difference in volume of the LA was the key characteristic of AF, multiple tests were conducted. First the volume of the LA was calculated for both AF and non-AF patients with the use of Python. The same libraries were used as before. To calculate the volume, I used the segmented portions of the LA in both the AF and non-AF datasets. All slices were used for each image. These images contained white spaces where the LA was and black spaces elsewhere. Therefore, the color of the pixel could be used to determine whether a section of the image was part of the LA or not. RGB values were used to quantify the white area of the image. Since the RGB value of black is equal to 0, any RGB value greater than 0 would be added to a counter, which totaled up the number of white pixels in each slice of heart. To convert from pixels to mm^3, since the resolution of the images for the AF cases was 0.625 x 0.625 x 0.625 mm^3, I multiplied the total for each case by 0.625^3 to obtain the accurate value [5]. The resolution for the non-AF cases was 1.25 x 1.25 x 1.37 mm^3, so I divided each of these totals by 1.25 twice, then by 1.37 to obtain accurate non-AF Left Atrial volumes [6]. I then calculated the mean of the AF and non-AF volumes separately in order to conduct a Two-Sample T-Test for difference of means to see if there was a significant difference in the volumes of LA between AF and non-AF patients. The final results are presented in the Results section.

The next step was the pre-processing of these images into an AI algorithm. The same images as before were utilized in this step (training set from both datasets). The TensorFlow and sklearn classes were key in this step for training the AI. The images and their corresponding masks were used during the pre-processing step. Both the images and masks were resized to enhance the performance of the AI. A U-Net Convolutional Neural Network was used to train the AI, that way it could break the image down into pixels and process its structure. After the AI was trained, the testing set was used to test whether the AI was accurately predicting AF and non-AF images. The model displayed an accuracy of about 98.77%.

Results:

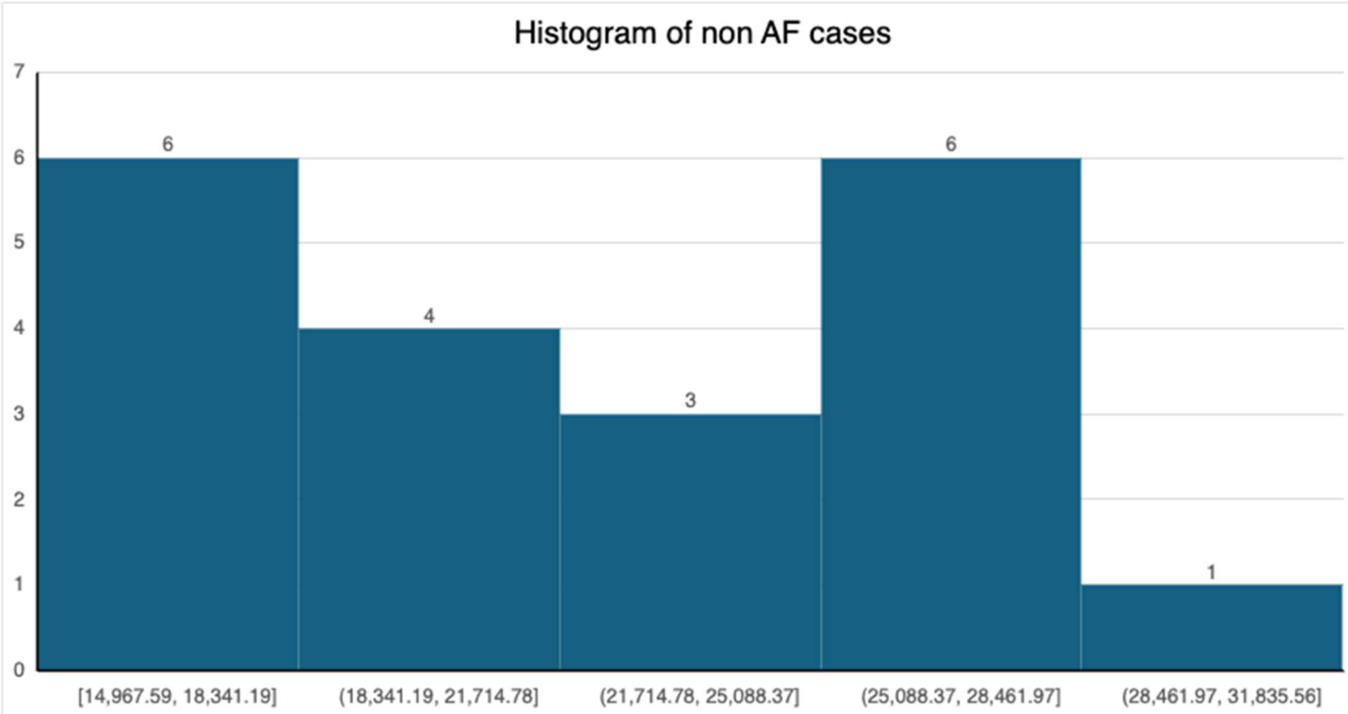

Figure 3: Distribution of the volumes of non-AF LAs

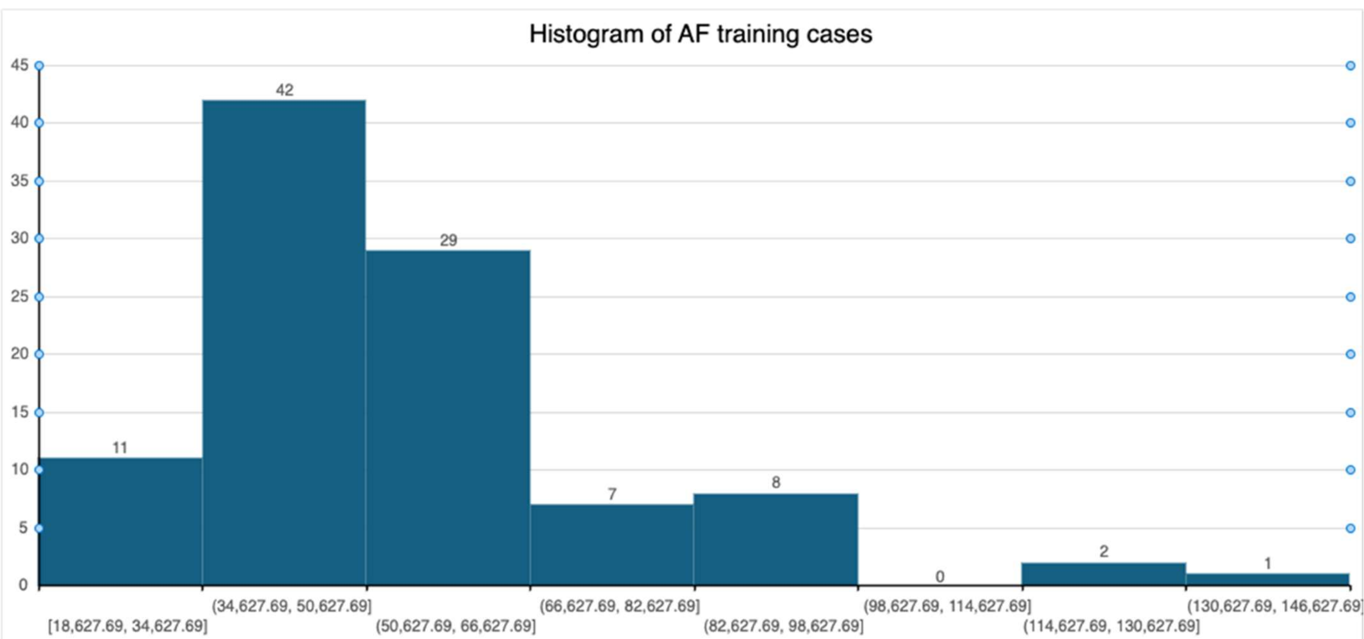

Figure 4: Distribution of all Left Atrial volumes of AF Training Cases

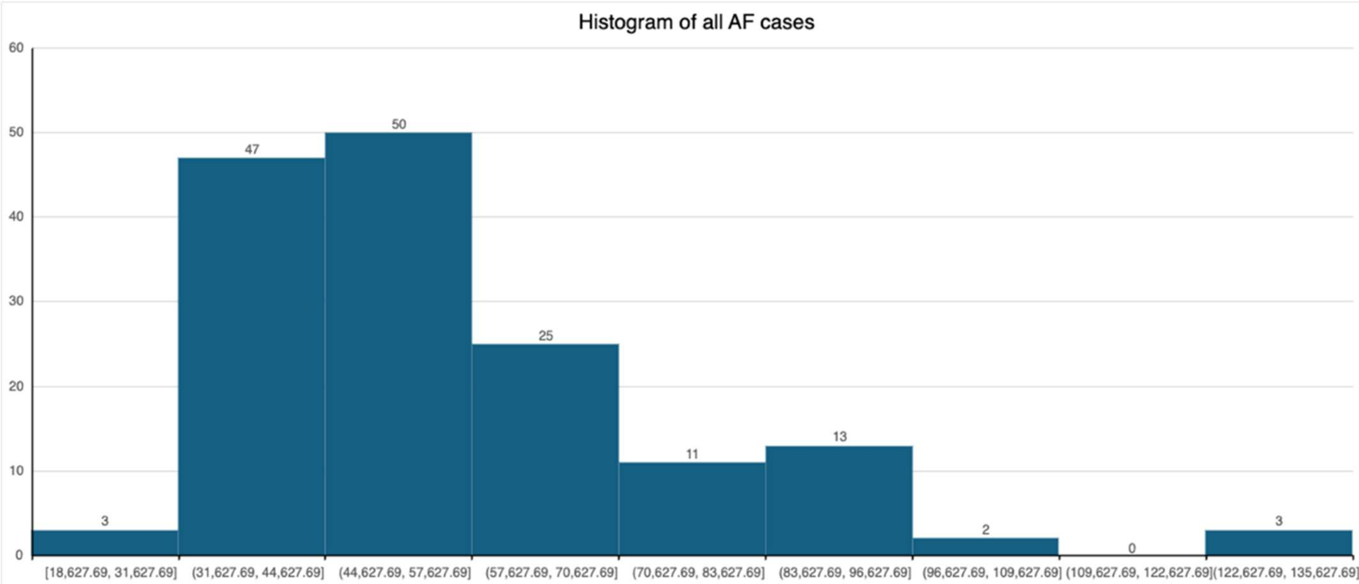

Figure 5: Distribution of the Left Atrial volumes of all AF cases

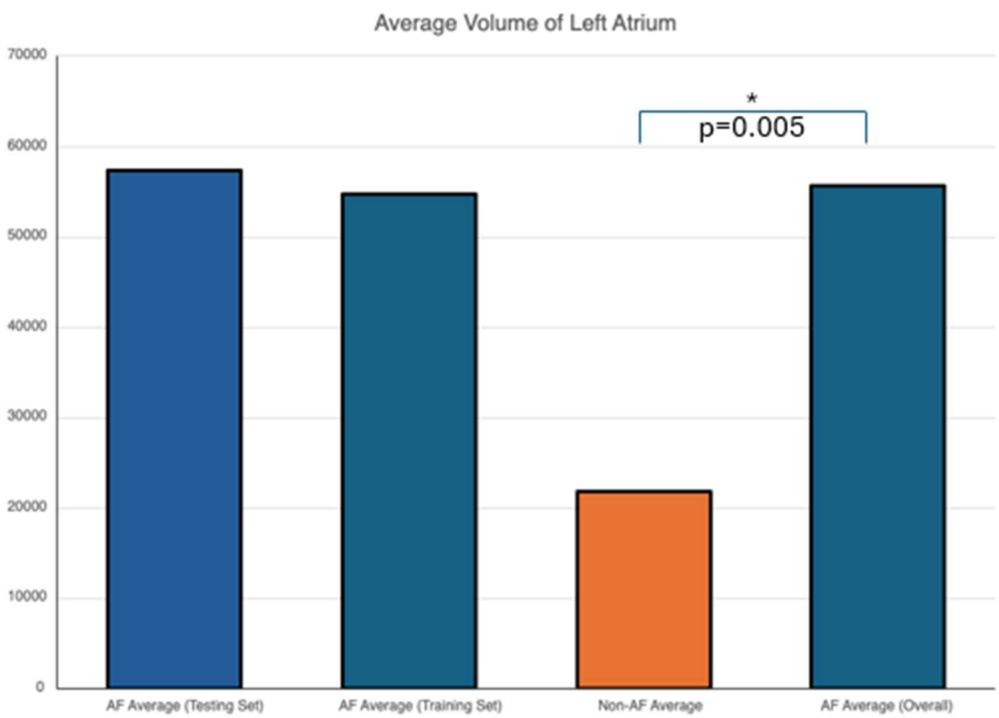

Figure 6: Average Left Atrial volumes of all cases. Significance test resulted in a p-value of 0.005, indicating a significant difference between Left Atrial Volumes between AF and non-AF cases

The average volume of the LA for patients diagnosed with AF was 55649.42 mm³. The testing set AF average was 57359.72 mm³ and that of the training set was 54725.86 mm³. These averages were much higher than the non-AF Left Atrial average of 21839.77 mm³. A significance test (Two Sample T-Test for difference of means) was conducted to verify whether this difference was statistically significant. With a significance level of 0.05 and p-value of approximately 0.005, there is enough evidence to conclude that the Left Atrial volumes of those diagnosed with AF is significantly higher than those without AF. However, this difference is not true for all AF cases. The distribution of AF Left Atrial Volumes displayed far more variability than that of non-AF cases. Even though the average Left Atrial volume for AF patients was about 36000 mm^3 greater than that non-AF cases, there were some AF cases with Left Atrial volumes below 30000 mm^3. This shows that, although usually the volumes of the LA for AF cases are significantly greater than non-AF diagnosed LAs, we must also consider other conditions of the heart such as inflammation, electrical activity, contraction, and damaged tissue. This is especially important when diagnosing patients with normal Left Atrial volumes.

Discussion & Conclusion:

AF is the most common type of heart arrhythmia, with about 5% of the adult population (over 10 million adults) being diagnosed with it as of September 2024. This disease doubles the risk of mortality [7]. It is characterized by an irregular heartbeat and an increased size of the LA. This disease has been increasing in prevalence over the past decade, and diagnosing the disease has proven to be a challenge. However, with image segmentation and the use of Artificial Intelligence models, this disease can be diagnosed in a matter of minutes. This method will reduce financial burdens on the medical industry by millions of dollars and is far more effective in diagnosing patients with the disease, as seen with the 98.77% accuracy in the model used for this experiment. Additionally, AI models can be trained to detect the severity of the disease through multiple series of simulations. Simply analyzing the volume of the LA is not always the deciding factor of whether a patient can be diagnosed with AF. That is why AI models are trained to analyze each segment of an image down to the pixel to ensure accuracy in diagnosis. This helps in detecting features like inflammation, tissue damage, and analyzing the frequency of heart contractions through multiple images. With this new method of identifying AFs, treatment options can become more readily available to suffering patients and research institutions can focus more on treatment options rather than diagnosis of the disease. Supervision of these models by health experts would still be necessary to account for any margin of error, but technological advancements will work to reduce this error significantly over the coming years.

References:

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