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Towards AI Based Diagnosis of Rheumatic Heart Disease: Data Annotation and View Classification

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Abstract: Rheumatic Heart Disease is a cardiovascular disease highly prevalent in developing countries partially because of inadequate healthcare infrastructure to treat Group A streptococcus pharyngitis and thereafter diagnose and document every case of Acute Rheumatic Fever, the immune-mediated antecedent of rheumatic heart disease. Secondary antibiotic treatment with penicillin injections after a diagnosis of Acute Rheumatic Fever and Rheumatic Heart Disease is used to prevent further attacks of Strep A, preferably prior to any heart valve damage. Echocardiographic screening for early detection of Rheumatic Heart Disease has been proposed as a method to improve outcomes but it is time-consuming, costly and few people are skilled enough to reach a correct diagnosis. Machine Learning is an emerging tool in analysing medical images; our aim is to automate the screening process of diagnosing rheumatic heart disease. In this paper, we present a web application to be used to label echocardiography data. These labelled data can then be used to develop machine learning models that can classify echocardiographic views of the heart and damaged valves from the echocardiograms.

Keywords: Acute Rheumatic Fever, Rheumatic Heart Disease, Echocardiograms, Machine Learning

1. Introduction

According to the World Health Organization (WHO), cardiovascular diseases are the leading cause of death in the world [1]. In 2019, 17.9 million people died from cardiovascular diseases, which was 32% of all global deaths [1]. Cardiovascular diseases affect the heart and blood vessels and they include: coronary heart disease, rheumatic heart disease, cerebrovascular disease, congenital heart disease and peripheral arterial disease. Three quarters of cardiovascular disease deaths occur in low- and middle-income countries [1]. It is important to detect cardiovascular diseases early so that management of the disease can begin. Unfortunately, people living in low- and middle-income countries do not have the benefit of primary health care facilities and programmes for early detection and treatment, leading to late detection or premature death of youth in their most productive years [1]. In this paper, we will focus on rheumatic heart disease (RHD).

RHD is a cardiovascular disease caused by damage to the heart valves from inflammation and scarring caused by repeat episodes of rheumatic fever [2]. Rheumatic fever is caused by an autoimmune body response to a strep throat caused by Group A streptococcal bacteria [2]. It mostly affects children in developing countries where poverty is widespread and bacteria can easily be transmitted [2]. RHD predominantly affects the mitral and aortic valves, which are found on the left side of the heart, causing valvular thickening on the tips of the leaflets. Thickening of the heart valves leads to regurgitation/stenosis, a case where the valves do not close properly with resultant backflow of blood or narrowing of valves resulting in restricted blood flow respectively. This could eventually lead to atrial fibrillation or heart failure.

The majority of patients with RHD in low and middle-income countries present with established disease [3], often with multi valve involvement. The opportunity to diagnose RHD at a subclinical or latent phase has long been suggested as a substantive prevention measure. Recently the GOAL study [4] demonstrated that penicillin prophylaxis applied to latent RHD as diagnosed by doppler echocardiology is associated with decreased progression (no worsening of disease) compared to those not on prophylaxis with latent RHD. The criteria for Latent or subclinical disease have been defined by a group of experts and described in the World Heart Federation (WHF) Guidelines [5] for RHD in asymptomatic populations.

The WHF diagnostic criteria for subclinical rheumatic heart disease include valve thickness as one of the morphological criteria [5]. Another criterion used is the velocity of the mitral and aortic valve's regurgitant jet velocity and length in at least two views, including the parasternal long-axis view [5]. The criteria recommended by the WHF for pathological mitral and aortic regurgitation include colour Doppler seen in two views [5]. Studies show that using the parasternal long-axis view and one other view with a colour doppler achieves 90% accuracy in the diagnosis of rheumatic heart disease [6]. Thickening of the mitral and aortic valves, a feature of RHD [6], can be examined by strict measurement of the mitral valves on the parasternal long-axis view. [7]. Of note, the position of the transducer and the orientation of the plane through the heart gives several echocardiographic views including parasternal long-axis, parasternal short axis, apical four-chamber, apical five-chamber and suprasternal view [7].

In this paper, we will focus on the parasternal long-axis view to analyze the thickness and motion of the mitral valve and colour doppler to assess for mitral regurgitation.

1.1 Population Risk, Prevention & Treatment

Children aged between 5 and 15 years are at a greater risk of getting rheumatic fever if they have frequent strep throat infections or a family history of RHD/ARF [8]. It may take years for symptoms of RHD to be noticed and when they develop, they depend on which heart valves have been affected, the type and severity of the damage. Symptoms of RHD include: shortness of breath, fatigue, irregular heartbeats and chest pain, as many as 40 million people are affected with over 350 000 dying of this disease annually.

RHD has no cure, but preventing rheumatic fever from reoccurring makes it preventable. Treating strep throat with penicillin will prevent recurrent rheumatic fever episodes [1], [9]. If RHD valve disease is advanced, surgical intervention for valve repair or valve replacement with either a mechanical or a prosthetic valve is recommended [10]. Repair is less invasive and eliminates long-term requirements for anticoagulants [10]. In developing countries where RHD is rampant, strategies such as ensuring a consistent supply of antibiotics, improving standards of living, and improving access to healthcare should be implemented [1].

1.2 Screening for Rheumatic Heart Disease

In the past, rheumatic heart disease was diagnosed by listening to heart murmurs in patients with a history of acute rheumatic fever using a stethoscope [5]. The stethoscope was the only non-invasive method available in developing countries and remote areas where rheumatic fever and rheumatic heart disease are most common [5].

Echocardiography has proven to be a more accurate method compared to the listening of heart murmurs, where detection rates are usually low [5]. Screening echocardiograms can detect rheumatic heart disease in its early stages, therefore creating an opportunity to limit progression of RHD [11].

With the emergence of portable echocardiography machines, screening can be done at a relatively low cost, even in remote areas. This will increase the possibility of previously undiagnosed cases of rheumatic heart disease being diagnosed and preventive measures started at earlier stages, therefore reducing mortality [5].

Echocardiographic screening for rheumatic heart disease meets many requirements for cardiovascular disease screening. Screening to detect asymptomatic cases is an excellent strategy because secondary prevention through penicillin injections can prevent recurrent attacks of acute rheumatic fever, resulting in no disease in 5-10 years [5].

1.3 Classification of Medical Images Using Machine Learning

Healthcare data is continuously increasing and diagnostic decisions significantly rely on digitized information, such as echocardiograms and electrocardiograms. These data in the form of images, wearable sensors and medication lists are large quantities of data which exceed the capacity of the human mind. The knowledge, interpretation, skills and experience with medical data varies from one medical practitioner to another, but machine learning algorithms can help in interpreting healthcare data from different sources and make it easier to diagnose patients [12]. Using supervised machine learning techniques, we can use echocardiograms and their corresponding labels to train a machine learning model and test it on echocardiograms never seen before.

2. Objectives

This project is aimed at automating the screening process for the diagnosis of rheumatic heart disease. The objectives of the project are:

1. Develop a web application that allows trained personnel to label echocardiograms with relevant metadata for RHD diagnosis
2. Create a machine learning ready dataset of echocardiograms for training of RHD diagnosis models
3. Train an echocardiogram view classifier

3. Methodology and Technology Description

We developed a web application to be used by cardiologists and experts on echocardiographic screening to label data for the valve damage classifier. The web application is based on Dash and is deployed on google cloud platform (GCP). It is being used to label the echocardiography data we have based on the view of the echo, the thickness state of the valves, the RHD conditions seen in the echo and the severity of RHD. We save the labels from the web application in a MySQL database hosted on the GCP. We will use these data for a multiclass view classifier and the valve damage classifier.

3.1 Dash

Dash is a python framework for building interactive web analytic applications written on top of flask, Plotly.Js, React.Js. It is ideal for building data visualization apps with custom user interfaces in Python, R, Julia, or MATLAB. Dash is open-source and applications built using Dash are rendered on a web browser [13].

Dash applications comprise two building blocks, the layout and callbacks. The layout describes the look of the app and defines elements such as drop-downs and the size, colour and placement of elements [13]. Callbacks are used to bring interactivity to the app. These are functions which can be used to define the activity that would happen by clicking a button or a drop-down. Callbacks have been used to select options for drop-down elements and to save the data collected in a MySQL database on the click of a "Save" button.

3.2 Google Cloud Platform (GCP)

Google Cloud Platform is a collection of cloud services such as computing, storage, big data, machine learning, internet of things and developer tools offered by Google. Some of the GCP products used for this project include Google App Engine and Google Cloud Storage [14].

Google App Engine is a platform-as-a-service (PaaS) that gives developers access to Google's hosting. Developers can use a software developer kit (SDK) to develop products that run on the App Engine. Google Cloud Storage is a cloud storage platform designed to store large datasets. Google also offers database storage options, including Cloud SQL [14].

3.3 Cloud SQL

Cloud SQL provides a cloud-based alternative to local MySQL, PostgreSQL and SQL databases. Cloud SQL manages your database and lets you focus on your data. A virtual machine running on a host Google Cloud Server [15]. A static IP address is available for every virtual machine to make sure any application connecting to it persists throughout the lifetime of the Cloud SQL instance.

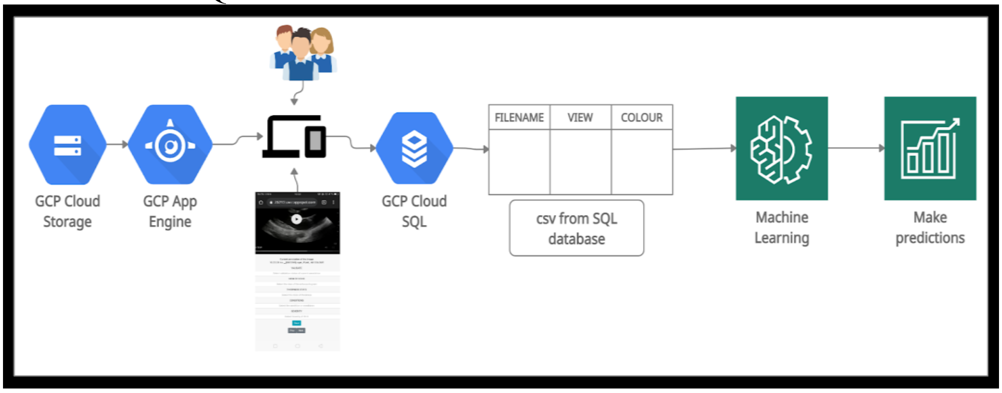

Figure 1. Architecture of the web application showing cloud computing services used (cloud storage, app engine and cloud SQL), the layout of the web app, and collected data from the web app.

3.4 Machine Learning

Machine Learning is a branch of AI which focuses on the use of data and algorithms to imitate the way humans learn, gradually improving its accuracy. Through the use of statistical methods, algorithms are trained to make classifications and predictions. Having more data gives your machine learning algorithm a higher chance of learning patterns from your data, then gives accurate predictions to unseen data.

3.4.1 Logistic Regression

Logistic regression is a supervised machine learning algorithm used for binary classification problems. We will use this to classify the views of the echocardiograms as either a parasternal long axis view (PLAX) or NOT PLAX. For a binary classification problem, the probability of class C_1 can be written as a logistic sigmoid acting on a linear function of the feature vector, ϕ [16]:

$$p(C_1|\phi) = y(\phi) = \sigma(w^T\phi) \quad \text{........ (1)}$$

Where σ is the logistic sigmoid function and the probability of class C_2 is given by:

$$p(C_2|\phi) = 1 - p(C_1|\phi)$$

The model in Eq. 1 is called the Logistic Regression in statistics. The logistic sigmoid function is defined as: $\frac{1}{1+e^{-a}}$
We learn the parameters of the binary classifier from the data we have.

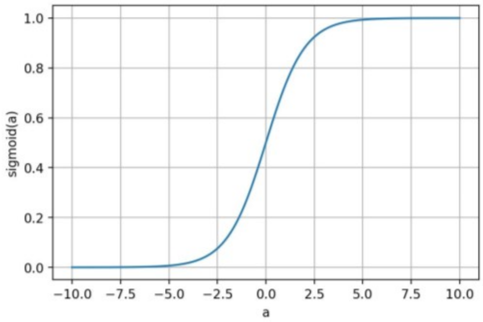

Figure 2. Sigmoid Function

3.5 Image Processing

Pre-processing data in machine learning is important because the quality of data and the useful information that can be derived from it directly affects the ability of our model to learn. Our data comprises 941 images (jpg format) and 852 videos (mp4 format) provided by a Paediatric cardiologist and RHD expert. One of the most important ethical standards to uphold in healthcare is patient privacy and confidentiality which we considered while setting up our data pipeline.

To prepare our image data, we used techniques such as image resizing and converting images to grayscale to reduce computation complexity. We extracted frames from the videos of echocardiograms we have resulting in 52658 images. We cropped these images to remove patient information then resized to 80x60. The resized images were then converted to grayscale and used to train and test our binary view classifier.

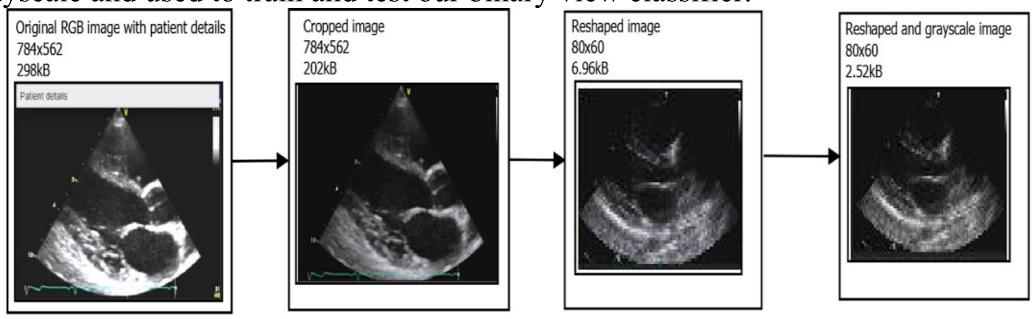

Figure 3. Data Pipeline Showing Stages of the Image Data while Pre-Processing

5. Results

From the web application, we have 43 entries of labelled images and videos of echocardiograms so far; 22 images and 21 videos. Figure 4 shows a distribution of the annotations done on the web application by a cardiologist. With these labelled data we have more echocardiographic views represented; parasternal long axis, parasternal short axis, subcostal, doppler and the Apical Four chamber views.

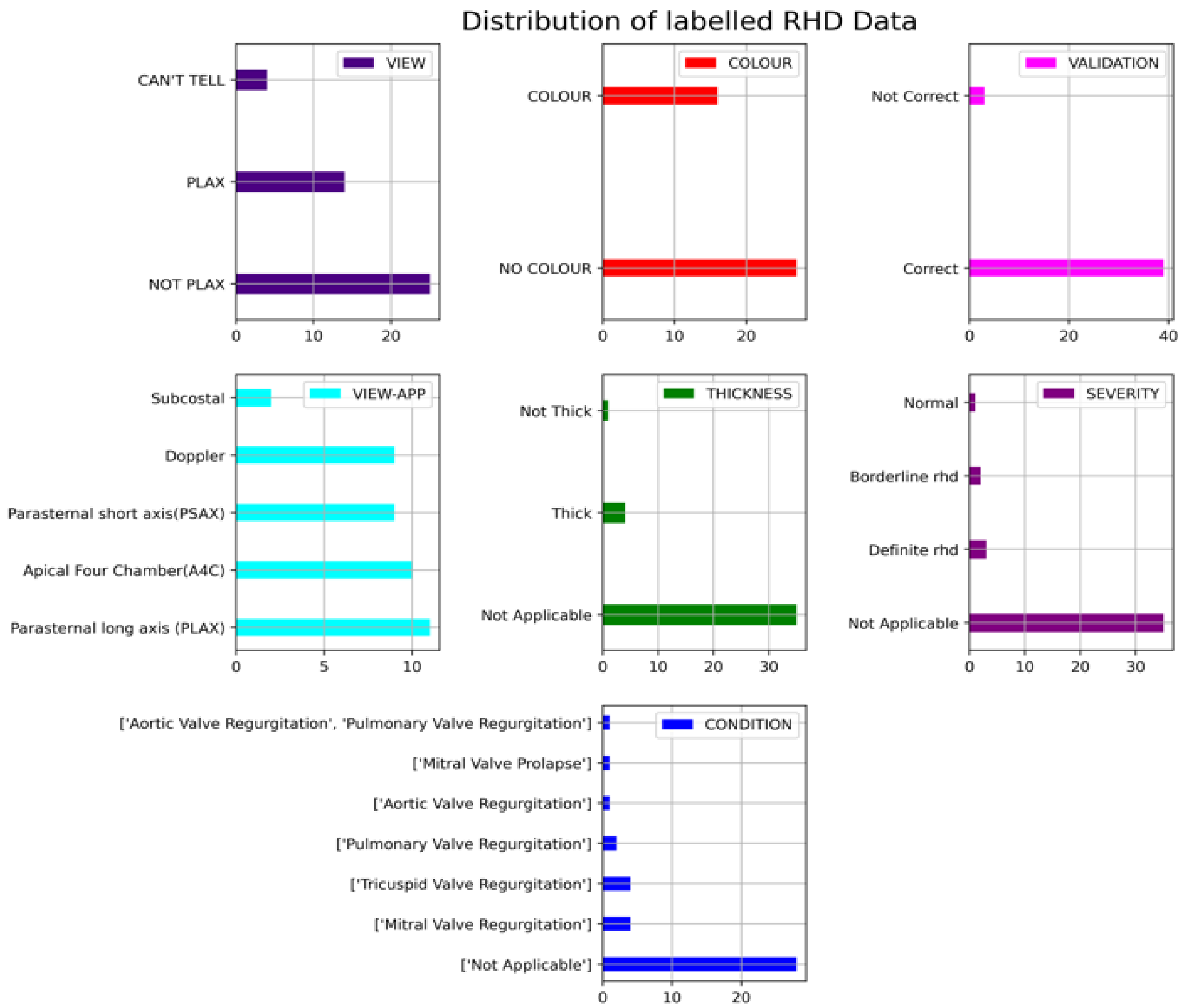

Figure 4. Distribution of annotation from the web app. The fields included were views of the echocardiograms, whether there was a regurgitant jet present (showed by presence of colour), whether the initial data annotation of the PLAX view by the first author was correct or not, Views of the echocardiograms as seen by a cardiologist, thickness state of the valves, severity of RHD and RHD condition the patient has.

For the binary view classifier, we used data not labelled by an expert since it was easy to classify the view of the echocardiograms as either PLAX or NOT PLAX. This data comprising 52,658 images was imbalanced with 15428 images having a parasternal long axis (PLAX) view, 36888 images with views that were not PLAX and 342 images that were not clear enough to be classified. We used 52316 images with a 70:30 split performed on the dataset to generate the train and test data. Data contained in the train and test dataset are 36621 and 15695, respectively. Using Logistic Regression, we were able to develop a binary view classifier for PLAX/ NOT PLAX. The unclear images were used as test samples and all were predicted as NOT PLAX views.

Table 1. Classification metrics from our binary view classifier

Accuracy	99.8%
Precision	99.7%
Sensitivity	99.5%
Specificity	99.9%

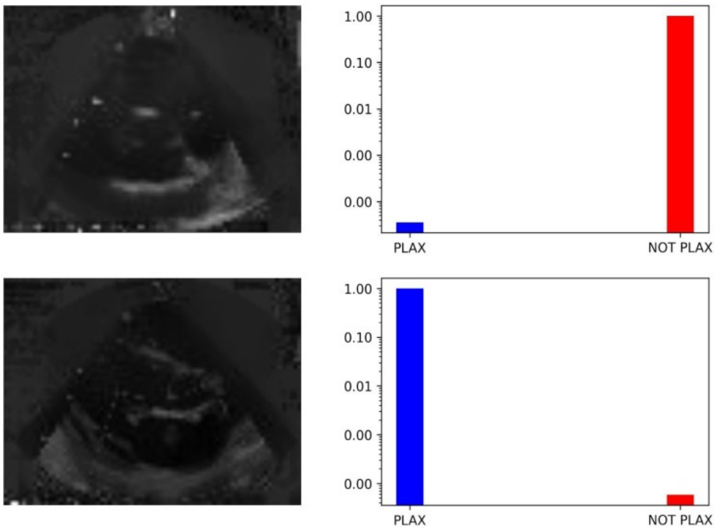

Figure 5. (a) An echocardiogram with a NOT PLAX view and corresponding bar plot showing the probability it is NOT PLAX. (b) An echocardiogram with a PLAX view and corresponding bar plot showing the probability it is PLAX.

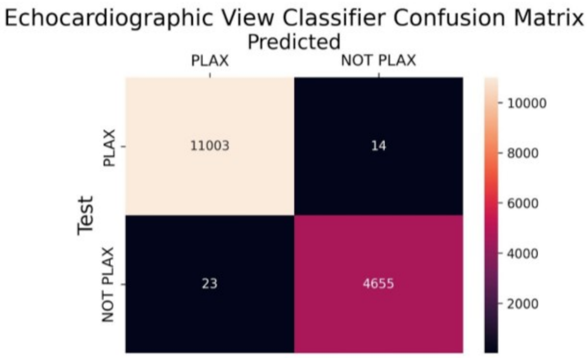

Figure 6. Confusion Matrix

6. Business Benefits

The field of medical AI is also continuously growing, and it has a huge financial potential. AI could help medical professionals design treatment plans, assist in monotonous jobs and manage the exponentially growing data in the form of medical records in healthcare.

7. Conclusions

The focus of this paper is on data acquisition to enable training of a machine learning model. Having enough and properly labelled data greatly influences the results of your machine learning model. Developing the web application to have our data labelled by experts in the cardiology field was a wise decision, as the results of the binary echocardiographic view classifier show.

This classifier was developed as a first step since it was easy to label the echocardiogram views as either PLAX or NOT PLAX, without experience in analyzing echocardiograms. Once all the echocardiograms are labelled by the experts using the web application, we will develop a Multiview echocardiographic view classifier. We can also proceed with developing a valve damage classifier and together with the latter, we can start our journey to automating screening echocardiograms for RHD. This can be used as a first step in determining whether further tests are necessary and if rheumatic heart disease is detected in younger patients early enough, then medication can be administered. This will reduce the burden of RHD in our communities and reduce mortality due to RHD.

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