Early Diagnosis of Heart Disease Via Google's AutoML

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ABSTRACT

Coronary heart disease is a leading cause of death around the world. Early and accurate detection of this disease is vital to reducing complications and preventing heart failure and heart attacks. This project creates an early-level diagnosis method that analyzes heart sound audio to detect and characterize heart anomalies including murmurs, arrhythmias, and extra heart sounds. The dataset was obtained from Peter Bently's Classifying Heart Sounds Database [1]. This dataset was used to train a machine learning algorithm in Google's AutoML Vision that could distinguish between normal heart sounds, murmurs, arrhythmias, and extra heart sounds. The final model has an average precision of 0.929, thus providing accurate results. This product can be used as a cheap, accessible, and non- invasive diagnosis method for the early detection of cardiovascular diseases.

Introduction

Cardiovascular diseases are the number one cause of death around the world. A subtype of cardiovascular disease, coronary heart disease, kills an estimated 7.2 million people yearly. Of the deaths, 75% occur in low and middle-income countries [2]. Early detection of CHD can reduce complications of the disease, including heart failure, stroke, and kidney failure [3]. Because of this, detecting signs of heart disease, especially early in their development, can significantly impact world health. In addition, abnormal heart rhythms such as murmurs, arrhythmias, and extra heart sounds all signify problems within the heart [4]. So, heartbeat sound classification is an efficient tool for diagnosing heart diseases.

Currently, the diagnosis of coronary heart disease can be made through a stethoscope, ECG, echocardiogram, or angiogram. The most common instrument used to diagnose CHD is a stethoscope. Using a stethoscope, experienced medical professionals can listen to heartbeat sounds and determine if a patient is healthy or not [5]. But, there are problems with this practice. A study examining 453 physicians in training and 88 medical students found that, on average, internal medicine and family practice residents recognized only 20% of all cardiac events [6]. This suggests that a better alternative to doctors using stethoscopes is needed.

Different heartbeat types have different patterns. For example, a normal heartbeat consists of a "lub dub, dub lub" pattern; a murmur heartbeat has whooshing, roaring, and rumbling sounds; and an extrasystole heartbeat has an out-of-pattern beat such as "lub-lub dub, lub dub-dub." [7] In this project, we aim to create an early-level diagnosis method that analyzes heart sound audio to detect and characterize heart anomalies. This application will make an early diagnosis of heart disease more accessible to people without readily available medical care, which can mean the difference between life and death.

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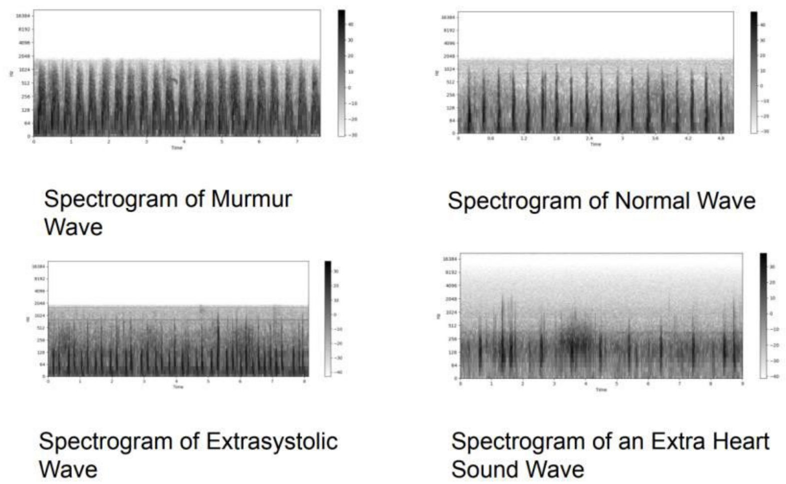

Figure 1: Spectrograms of different heart anomalies (murmur, extrasystolic, and extra heart sound) compared to a normal heartbeat.

Materials and Methods

Data Set Creation:

The dataset used to train this program was from Peter Bently's Classifying Heart Sounds Database. The dataset contained images and was collected from two sources: iStethoscope Pro iPhone app (Data Set A) and from a digital stethoscope used in clinical trials (Data Set B). A custom python script was created to convert the audio files into spectrograms.

Model Creation:

The model was trained to distinguish between 8 categories:

1. Extrahls
2. Seta_artifact
3. Seta_mumur
4. Seta_normal
5. Setb_murmur
6. Setb_noisynormal
7. Setb_normal
8. Setb_extrastole.

To increase the size of the dataset, random data augmentation was applied by speeding up and slowing down audio recordings by a factor of 1.5.

Several Models were tested:

a. The first model had 534 images and had:
   i. Average precision = 0.757
   ii. Precision = 72.73%
   iii. Recall = 61.54%

To increase the recall accuracy of my model, the model was trained to avoid false negatives. To accomplish this goal, the dataset was increased by applying random data augmentation. Any labeling errors in the data were fixed.

b. The second model had 550 images and had:
   i. Average precision = 0.830
   ii. Precision = 79.59%
   iii. Recall = 68.42%

c. The final model contained 656 images and had:
   i. Average precision = 0.929
   ii. Precision = 87.5%
   iii. Recall = 79.03%

Results and Discussion

The final design was trained with 16 nodes, contained 656 images and had an average precision of 0.929

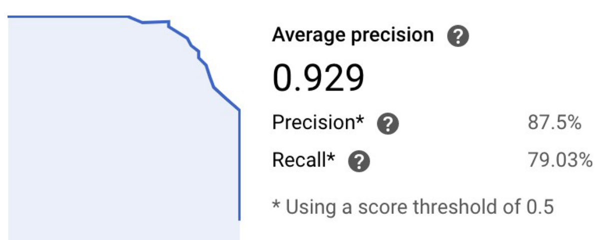

Figure 2: At a confidence threshold of 0.5, there is an average precision is 0.929 with a precision of 87.5% and a recall of 79.03%. A high precision model produces few false positives, and a high recall model produces few false negatives.

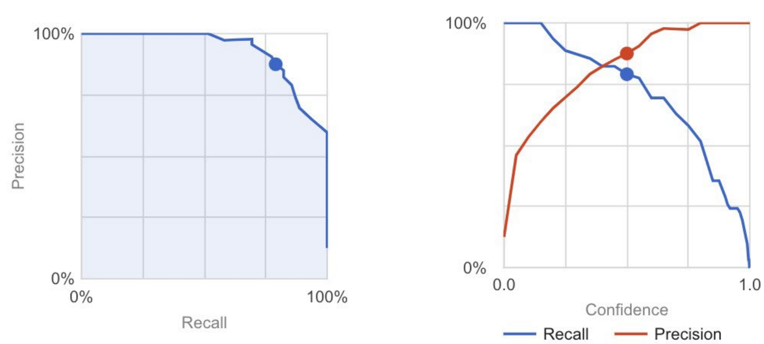

Figure 3: Graphical representation of Precision and Recall

Current research efforts include machine learning classification algorithms such as ensemble methods, deep learning and clustering techniques. This study explores the use of machine learning, specifically Google Cloud's AutoML, as a possible method for the diagnosis of heart disease. As shown by the results, the use of AutoML has high accuracy and precision. A limitation to this study was the size of the dataset. To improve upon results, a larger data set with a greater number of images and a greater variety of images can be used.

Conclusion

The final design prototype met all the criteria in the hypothesis. The algorithm accurately predicted the types of heart abnormalities with an average precision of 0.929, an overall precision of 87.5% and an overall recall of 79.03%. Precision is a measure of quality, and recall is a measure of quantity. The higher precision means that the algorithm returns more relevant results than irrelevant ones, while recall means that it returns most of the relevant results whether irrelevant ones are also produced. In the case of medicine, it is better to have a high precision model focused on quality than a high recall focused on quantity. This model is a cheap and accessible apparatus that can be used to detect heart abnormalities to diagnose heart diseases. Although it is not meant to replace medical assessments, it can allow users without access to medical attention the ability to recognize heart anomalies to determine if further treatment is needed.

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