Predicting left ventricular Ejection Fraction using Artificial Intelligence (AI) to save costs by using ECG over echocardiography

Introduction

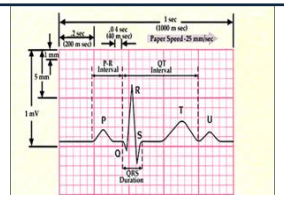
Echocardiography is a key noninvasive imaging technique used to determine the heart's pumping function, specifically by measuring the Left Ventricular Ejection Fraction (LVEF). While echocardiography is a crucial, noninvasive cardiac diagnostic tool widely used in developed countries, two-thirds of the world's population—roughly 5 billion people—lack access to basic diagnostic imaging, including echocardiography. My research revolved around creating an Artificial Intelligence (AI) program that would accurately determine ejection fraction using electrocardiography (ECG) which is 5 to 10 times less expensive than echocardiography, and widely available.

Question and Hypothesis

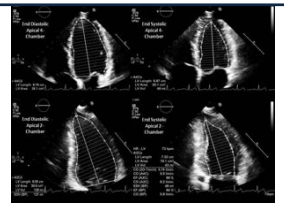
Question: Can AI predict LVEF based on ECG data?
Hypothesis: An AI model using ECG-derived numerical features (e.g., QRS and QT durations) accurately predicts LVEF

Background Research

Early clinical studies by Murkofsky et al. (1998) established that prolonged QRS duration (>100 ms) on ECG is a highly specific marker for left ventricular dysfunction, though not very sensitive. Later, Krüger et al. (2004) enhanced diagnostic accuracy by combining QRS duration with brain natriuretic peptide (BNP) levels, while Shenkman et al. (2002) and Kashani and Barold (2005) demonstrated that both QRS duration and morphology (notably LBBB) predict adverse outcomes including mortality—even in preserved ejection fraction. Wang et al. (2008) showed patients with prolonged QRS and low LVEF benefit most from Cardiac Resynchronization Therapy (CRT). Building on this foundation, modern AI research, such as the EchoNext dataset curated by Elias and Finer, uses paired high-quality ECG and echocardiogram data to train deep learning models that detect structural heart diseases directly from ECG signals with high accuracy, combining engineering, physiology, and machine learning innovation.



ECG $10-$50



Echocardiogram $ 1200-2000

Purpose: To develop an AI algorithm that would use age, sex, race, and 3 ECG derived parameters qrs-duration, qt-duration, and ventricular rate and predict ejection fraction, which would ordinarily require an expensive test – echocardiogram.

Methods and Materials

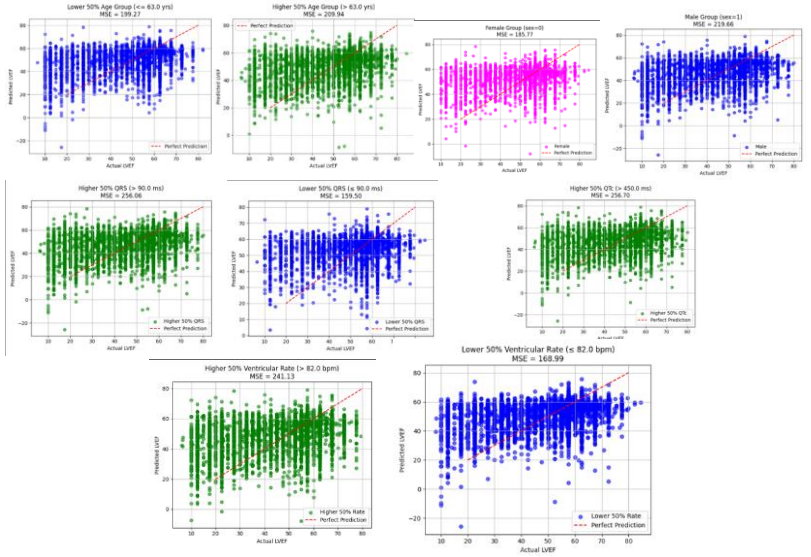
To conduct this experiment, you would have to acquire a computer with a CPU, the following programming (listed in this section), and some form of ECG data (collected or acquired).

Data collection:
My database - Echonext_metadata_100k_samples made by Pierre Elias and Joshua Fisher (9) - on Physionet, one of the largest medical database biorepositories. This database contains 100,000 samples from people in Boston from all backgrounds. The database contains information about age, gender, race, QT interval, QRS duration, heart rate as well as corresponding echocardiographic data including Ejection fraction (EF) with minimal bias.

Procedure

1. Sought approval for access to open-source database (EchoNext metadata) for ECG and Echocardiographic findings, including Ejection Fraction (EF).
2. Trained the AI on data from 100,000 patients derived from EchoNext data base which each has a unique value for LVEF, age, sex, race, QRS duration, QTc interval, Heart rate.
3. The first step in making the code was the input load, which interprets the metadata and turns it into a vector or 1 dimensional matrix.
4. In this first iteration, each value in each input value in the database gets appended as a numerical value to the layer (gender and race get numeric encoding). This is vastly inefficient as the cache (system which takes values in random access memory) has to go all the way through the database every time an index is called.
5. The next step in this neural network is the weight and bias vectors.
6. The final AI simplifies all of the redundant code into a single tuple which will be carried out in later processes and lead to the final trained weights and biases.
7. The next step is to establish activations and backpropagations - two different parts with a very intertwined relationship.
8. The model takes the layer sizes, trains them using more simple code, and goes through 200 epochs (2000 forward and backpropagation steps).
9. Overall, the AI had a final loss of 1.000002 (very optimal for L-BFGSs, indicating over 99.7% theoretical accuracy) and a runtime of 25 minutes and 43 seconds.
10. Upload all weight and bias vectors to flask and save it to a pickle file, and this is to save the AI to a place where you can easily refer back to it for testing and usability.
11. Create a system that tests the AI.
12. Upload new ECG information, so that it runs through the AI and test how accurate it is.
13. The AI was validated on data from 20,000 patients derived from EchoNext data base.
14. Results were plotted on graphs and accuracy calculated.

Data and Results



Conclusions

- The AI predicts Ejection Fraction (EF) with about 85% accuracy, working best around the normal EF range where both genders show strong clustering.
- It struggles a bit more with extreme cases, which lowers its true accuracy to about 77%.
- This AI can help predict EF using cheaper ECG tests instead of expensive echocardiograms, which could reduce healthcare gaps and improve care in underserved areas.

Sources

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