iCardo 3.0: Machine Learning Framework for Prediction of Conduction Disturbance in Heart

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Abstract. Cardiovascular disease is one of the main causes of death globally. Electrocardiography (ECG) is one of the non-invasive methods to assess the disorders of heart functioning. The paper presents the prediction of conduction disturbance or disorders (CD) which lead to chronic heart failure or cardiac arrest through a 12-lead electrocardiogram (ECG). A publicly available large electrocardiography data set named PTB-XL is used in the study. Bagging and boosting-based machine learning algorithms (i.e. Random Forest (RF) and XG boost along with the Support Vector Machine (SVM) have been used to classify the CD and normal subjects. Two demographic features, age and sex of the subject, have been added to the ECG to prepare the final data for the input of the classifiers. The performance in terms of accuracy with Random Forest(RF) and XG boost performance is similar whereas the total number of true predictions is higher in the case of RF.

Keywords: Conduction Disturbance · ECG · CVD · chronic heart failure · Random Forest · XG Boost · SVM

1 Introduction

Conduction in a human heart refers to how the electrical impulse travels within the heart, which causes it to beat. Normally the impulse generated by the Sinoatrial (SA) node activates the atria. The conduction pathways continue to bundle branches, i.e., Left Bundle Branch (LBB) and Right Bundle Branch (RBB), and finally cause the contraction of the left and right ventricles simultaneously. Each impulse contributes to one heartbeat. Depending on the individual's age, the heart typically beats 60 to 100 times per minute during resting. Conduction disturbance (CD) or disorder is a condition of the heart in which it has a block in conduction pathways. The conduction disorders lead to chronic heart failure. Conduction disorders can be broadly classified into three categories: First-degree heart block, Second-degree heart block, and Third-degree heart block [1]. In first-degree heart block, the electric impulse moves slower through the heart's atrioventricular (AV) node than normal. It does not cause any symptoms. In second-degree heart block, only some of the electrical impulses reach from the upper heart's chamber, that is, atria, to the lower heart's chamber, which is the ventricles. In this situation, the heart may miss beats, or the heartbeat may be irregular or slow. It has symptoms like heart palpitations, shortness of breath, chest pain, etc. In the third-degree heart block, also known as complete heart block, the electrical impulse can not pass from the heart's upper chamber to the lower chamber of the heart, but ventricles still contract and pump blood but at a slower rate. Although the contraction is not proper and the pumping of blood is also ineffective. In this situation, the patient requires immediate help as it has a high risk of cardiac arrest. Since CD disrupts the electrical impulse of the heart, it reflects in ECG, making the ECG a suitable tool for predicting CD. Since CD Some work related to this field is discussed in the next section **??**.

Many researchers in the field of prediction CD are coming off. It is discussed that first and second-degree heart blocks do not give idiosyncratic symptoms to have proper identification. Prediction of the CD at an early stage can decrease mortality. Conductance disturbances are quite common after Transcatheter aortic valve replacement (TAVR) [3][8]. A comparison of machine learning models and neural networks to predict Atrioventricular block with single lead ECG is presented by [6]. To predict the CD accurately after TAVR [5] presented an ML-based model for patient-specific monitoring. [4] assessed the risk factors of conduction disturbances, atrial fibrillation, sudden coronary death, and device infection. On the other hand [10] investigated conduction disorders and arrhythmia associated with the septal defects. [9] studied the Conduction disturbances in patients with systemic sclerosis. Here, in this paper CD is predicted with 12-lead ECG and two additional features i.e., 'age', and 'sex. The detail of the data used here is given in section 2, while detailed methodology is explained in section 3.

2 Dataset

A publicly available large electrocardiography data set named PTB-XL [7] has been used in this work, and it was taken from [2]. It contains 12 lead ECG recordings (i.e. (I, II, III, aVL, aVR, aVF, V1, V2, V3, V4, V5 and V6)) of 21837 records that have been taken from 18885 subjects, and each recording is ten second long. The ECG data is a multi-label data set as up to two cardiologists annotated it. Later it was aggregated as diagnostic super and subclass. Five superclasses are: Normal ECG (NORM), Conduction Disturbance (CD), Myocardial Infarction (MI), Hypertrophy (HYP) and ST/T change (STTC). Here only two classes are considered which are: NORM and CD. Conduction disturbance or disorder (CD) includes the following diseases:

– LAFB/LPFB : Left anterior/left posterior fascicular block
– IRBBB : eft anterior/left posterior fascicular block
– ILBBB: incomplete left bundle branch block
– CLBBB : complete left bundle branch block
– CRBBB : complete right bundle branch block

- AVB : AV block
- IVCB : non-specific intraventricular conduction block or disturbance
- WPW : Wolf-Parkinson-White syndrome

The data inclusion and exclusion for the presented work is shown in Fig. 1

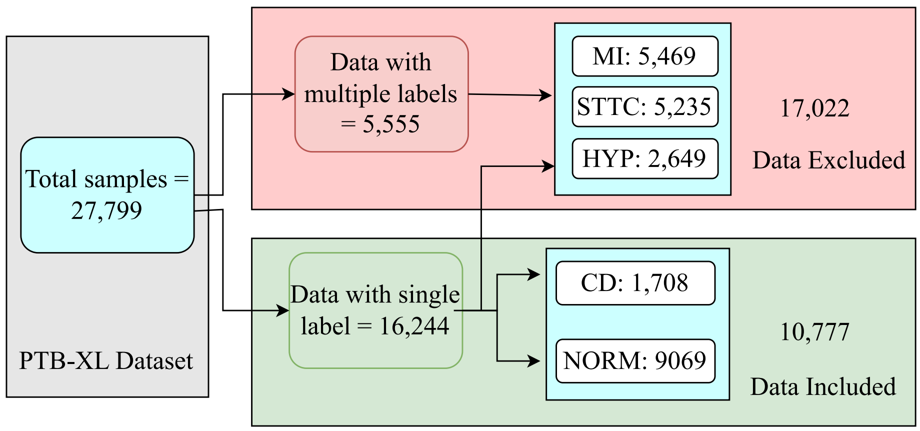

Fig. 1. Data Inclusion and Exclusion Process Flow

3 MLCardio : Proposed Machine Learning method

3.1 Data Preparation

The problem is modelled as a binary classification problem, in which class 1 is the normal subjects (NORM), and class 2 is the subject with CD. The 12-leads ECG data for all 10777 subjects have been converted into a 3-D array using Numpy in Python 3.0. Later it was flattened into a 2-D array and converted into a data frame using Pandas. After which, two features, 'age' and 'sex' have been added to the data. The training data are scaled or standardized with the help of Standard Scaler from the sklearn library. Finally, the prepared training data are used to train three different classifiers.

3.2 Machine Learning Models

Here, Support Vector Machine(SVM), due to its discriminative power of classification [11], along with the ensemble machine learning algorithm, i.e., Random Forest and XG Boost, are used for the prediction of conduction disturbances. The ensemble ML algorithms have two benefits in predictive modelling; (i) Performance, and (ii) Robustness. An ensemble ML model can make more accurate predictions and accomplish superior performance than any solitary model, and it also reduces the variance or dispersion of predictions. Adding two demographic features, i.e., 'age' and 'sex', to the raw ECG signal significantly improved the models' performance.

3.3 Classification of CD

The three classifiers, which are Random Forest (RF), XG Boost (XGB), and Support Vector Machine (SVM), are initialized with their default hyper-parameter and trained with the prepared data. After training, the testing data evaluate the models' performances. Overall accuracy, precision, recall, and f1-score are performance measures.

Performance Measures There are various performance measures for classification models, although the most common is accuracy. Here is the list of performance metrics evaluated for each machine-learning model:

- Accuracy: Ratio of correct prediction to total no. of prediction
- Precision: It is the ratio of True Positive (TP) to total positive prediction (i.e., the sum of TP and FP)
- Recall: It is the ratio of True Positive to actual positive (i.e., the sum of TP and FN)
- F1 score: It is the harmonic mean of precision and recall

All the above performance metrics are calculated for all the classifiers, i.e., SVM, RF, and XG Boost, and listed in the next section, and the process flow of the work is shown in Fig. 2.

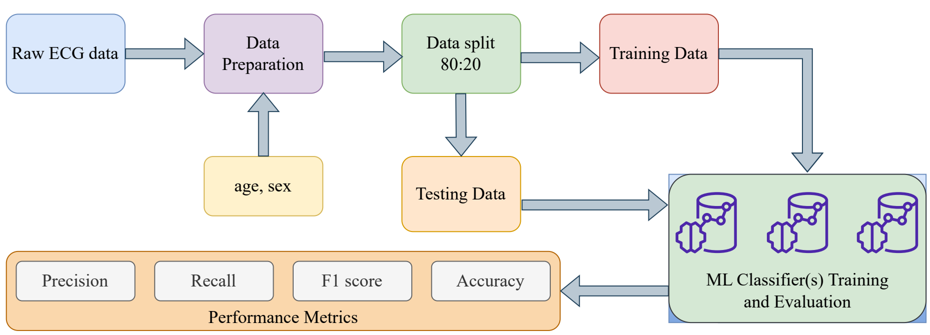

Fig. 2. Data Inclusion and Exclusion Process Flow

4 Results and Discussion

The data included for the work has 10,777 samples, which were split into training and testing sets. Eighty per cent of the data, which is 8621 samples, is used for training the model, while twenty percent of the data, i.e., 2156, is used for evaluating the model's performance which is also called testing. Two features, 'age' and 'sex' have been added to the ECG signal data before training and testing. These two features improved the classifiers' performance significantly. Usually, either the raw ECG signals or features extracted from it alone are used in ML classification. The limitations of such approaches are: If alone, ECG raw signals are used in ML, it gives low accuracy, and if it is used with neural networks, it requires comparatively more computation and resources. On the other hand, if extract features from raw ECG signals then apply the ML to classify, then it adds complexity to the model. Although, here in the presented work, raw ECG is combined with two readily available features, i.e., 'age' and 'sex.' which improves the classifier's performance significantly. The overall performance matrices of each classifier before and after adding the 'age' and 'sex' features are listed in table 1 2, and the confusion matrix for each classifier after adding 'age' and 'sex' features are given in 4.

Table 1. Performance metrics of SVM, XG Boost, and RF before adding 'age' and 'sex' features

ML Classifiers	Precision (%)	Recall (%)	F1 score (%)	Accuracy (%)
Support Vector Machine (SVM)	70	84	77	84
XG Boost	72	84	76	84
Random Forest (RF)	74	83	77	83

Table 2. Performance metrics of SVM, XG Boost, and RF after adding 'age' and 'sex' features

ML Classifiers	Precision (%)	Recall (%)	F1 score (%)	Accuracy (%)
Support Vector Machine (SVM)	89	87	83	87
XG Boost	89	90	88	90
Random Forest (RF)	90	90	89	90

Table 3. Confusion matrix of SVM, XG Boost, and RF respectively

	NORM	CD
NORM	1815	1
CD	279	61

	NORM	CD
NORM	1797	19
CD	206	137

	NORM	CD
NORM	1791	25
CD	189	151

It is evident that the ensemble ML algorithms perform better than the SVM, as we know that RF uses the bagging approach and works parallelly, while XG

Boost works on the concept of boosting, which is a sequential process. Then it can be concluded that RF is better in terms of speed and complexity as well as overall performance metrics. The performance measures for each class are listed in the table 4 for a better understanding of the classifiers' behavior.

Table 4. Class-wise performance metrics of each classifier after adding 'age' and 'sex' features

Performance Metrics	SVM		XG Boost		RF	
	NORM	CD	NORM	CD	NORM	CD
Precision	0.87	0.98	0.90	0.88	0.90	0.86
Recall	1.00	0.18	0.99	0.39	0.99	0.44
F1 Score	0.93	0.30	0.94	0.54	0.94	0.59

In future work, the neural network-based classifier can be studied. Apart from this, Optuna optimization can be performed on the presented ML models to improve the performance further.

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