Introducing the Electromechanical Risk Factor Score Derived from Seismocardiography for Estimating the Likelihood of Coronary Artery Disease

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Abstract

Non-acute cases of coronary artery disease (CAD) are initially assessed using pretest probability (PTP) scores, such as ESC2019 score recommended by the European Society of Cardiology. However, these scores often lack specificity, resulting in false-positive outcomes. This study aims to introduce a novel ElectroMechanical Risk factor Score (EMR Score) based on cardiac mechanical activities, derived from seismocardiogram (SCG), to reduce false positives in CAD detection.

SCG data, along with clinical risk factors, were collected from patients undergoing coronary artery evaluation. A total of 1360 patients were included in training dataset, with 622 of them exhibiting significant CAD, while the remaining 738 grouped as non-CAD. The test dataset consisted of 362 individuals in total, among which 62 were labelled as CAD. The EMR Score was developed using a one-dimensional Convolutional Neural Network (1D CNN) trained on SCG features, integrated with clinical variables.

The EMR Score outperformed the ESC2019 score, with an AUC of 79 % compared to 72%. The EMR Score exhibited significantly higher specificity (44%) compared to the ESC2019 score (24%) at a cutoff of 20%.

The EMR Score, incorporating SCG data and clinical risk factors, offers improved sensitivity and specificity for CAD detection compared to the ESC2019 score. This novel approach has the potential to enhance the accuracy of non-invasive CAD assessments, reducing the occurrence of false-positive results and improving patient outcomes.

1. Introduction

Coronary artery disease (CAD) is a common health condition distinguished by the constriction and stiffening of the arteries responsible for delivering blood to the heart. It stands as a major contributor to global mortality rates. The occurrence of CAD differs among diverse populations and nations, yet it remains a noteworthy global public health issue. Multiple risk factors play a role in the onset of CAD, such as an unhealthy diet, lack of physical activity, tobacco use, elevated blood pressure, increased cholesterol levels, diabetes, obesity, and a family history of the condition. When it comes to investigating of patients suspected of having CAD, there is a wide range of diagnostic methods available. These methods include blood tests, electrocardiograms, stress tests, imaging techniques (such as CT scans, MRIs, and nuclear imaging), and invasive procedures like coronary angiography. However, in general when a patient first experiences non-acute symptoms, they are initially assessed for risk of CAD bases on the different pretest probability (PTP) scores. A specific PTP score is outlined in the 2019 European Society of Cardiology guidelines for chronic coronary syndromes (ESC2019) [1]. Despite being an improvement compared to earlier scores like the Diamond–Forrester score, it still exhibits limited rule-out capability due to its high sensitivity and correspondingly low specificity. The main purpose of this study is to introduce a new score based on cardiac mechanical activities, with the specific aim of improving sensitivity while diminishing the occurrence of false-positive outcomes.

The mechanical activities of heart induce chest vibrations which can be measured with a accelerometer mounted on the sternum. The accelerometer non-invasively captures the linear acceleration, or seismocardiogram (SCG). An SCG is commonly recorded dorsoventrally using an accelerometer placed on the sternum close to the xiphoid process. SCG was initially recommended, in the early 1960s, for monitoring heart rate variability [2]. In studies conducted in the early 1990s, SCG was suggested as a non-invasive technology for detecting coronary artery disease [3]. Salerno et al. studied the morphology of exercise SCG in patients with $\geq$50% coronary artery stenosis [4] and reported significant changes in the morphology of SCG before and immediately after exercise, particularly during isovolumetric contraction up to the occurrence of aortic valve opening. Their findings suggested that exercise SCG in conjunction with 12-channel electrocardiog-

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raphy (ECG) improved the sensitivity of detection of coronary artery stenosis compared to ECG alone. In our recent study [5], we suggested that the analysis of SCG during rest can detect CAD without the need to stress the heart.

For the purpose of this study, we designed and trained a model using the electromechanical activity of the heart extracted from SCG, combined with clinical risk factors. The goal was to establish an ElectroMechanical Risk factor Score (EMR Score) that could be used to roll out the coronary artery disease. The model designed and trained over a dedicated training data set and was then evaluated using a separate and independent test dataset. We compared the EMR Score with ESC2019 score.

2. Material and Methods

The study involved recording the cardiac electromechanical activity of patients in supine position for 5 minutes using the HeartForce CardioClin device, which combines ECG and SCG signal acquisition. The device was securely placed on the sternum, and data from three axes (x, y, z) were collected at a sampling rate of 250 Hz with 16-bit precision.

2.1. Dataset

In this study, coronary artery disease (CAD) was defined as the presence of more than 50% stenosis in at least one coronary artery, as established through invasive coronary angiography (ICA) or coronary computed tomography angiography (CCTA). The training dataset encompassed a total of 1366 patients, among whom 622 exhibited significant CAD, while the remaining 738 labelled as non-CAD, as determined by the results of ICA or CCTA tests. Furthermore, the test dataset consisted of 362 individuals in its entirety, with 62 individuals diagnosed with CAD and 300 individuals classified as non-CAD cases based on their CCTA findings.

2.2. ESC2019 Score

The PTP score, recommended by ESC2019, is based on the updated Diamond-Forrester approach and utilizes age, sex, and symptoms as predictive variables. In this study, the PTP scores were obtained from Table 5 in the study by Knuuti et al. [1]. We will refer to this score as the ESC2019 score for now on.

2.3. SCG Features

Our analysis focused on the first 30 seconds of the SCG signal for each subject. To prepare the data for analysis, we applied a zero-phase band-pass Butterworth filter with an order of 5 and a band-pass frequency range of 0.5-40 Hz to each axis of the SCG. This filtering approach was chosen to eliminate low-frequency baseline wander attributable to respiration, higher frequency noise, and artifacts associated with valve closure acoustics while preserving essential morphological features of the SCG. Following filtering, we subtracted the average from each signal and then normalized the signals to a range between 0 and 1. These preprocessing steps were executed to enhance the comparability and analytical robustness of the SCG signals across subjects.

To extract features from SCG signals, the following procedures were executed:

1. The continuous wavelet transform (CWT) was employed to analyze the frequency components of the SCG signal at each time sample, generating a 2D plane denoted as T, with dimensions 416 by 7500.

2. A wavelet-based ECG delineation algorithm was utilized to identify the ECG Q-wave, which indicates the onset of left ventricular depolarization.

3. Each time-frequency plane, T, was subdivided into smaller planes known as Tcycle, based on the ECG Q-wave. Each Tcycle represents the time-frequency characteristics of a cardiac cycle, and due to heart rate variability, these Tcycle planes have varying lengths.

4. To ensure consistency, each Tcycle was zero-padded along the time axis to reach a length of 400 points, resulting in a 2D plane measuring 416 by 400. Subsequently, each Tcycle was averaged along both the time and frequency axes, reducing its size to 40 by 40. These planes were then flattened into vectors, each containing 1600 elements.

2.4. Electromechanical Risk Factor (EMR) Score

The vector features extracted from SCG were used to train one-dimensional Convolutional Neural Network (1D CNN) classifier, so-called Electromechanical model (EM model). This model includes three convolutional blocks, two fully connected layers, and a Softmax output layer. It utilized ReLU activation, max-pooling, batch normalization, and dropout. The model has specific filter sizes and kernel sizes, and the Softmax layer predicted CAD and non-CAD classes.

Subsequently, the findings obtained from the EM model were integrated with clinical presentation variables (such as age, gender, and symptoms) and risk factors (including family history of CAD, smoking, dyslipidemia, hypertension, and diabetes) through the training of a logistic regression model.

3. Result

3.1. Model performance

The AUCs for the two models using the test dataset were 0.72 (0.67 - 0.76) and 0.79 (0.75 - 0.83) for ESC2019 and EMR scores, respectivley, showing increasing AUC for EMR score. In both training and test datasets, the EMR score outperformed the ESC2019 score (Figure 1).

The diagnosis accuracy in terms of sensitivity, specificity, predicted positive and negative values were calculated for ESC2019 and EMR score at cutoff of 5% and 20% respectively (Table 1). The results reaffirm the low rule-out power of the ESC2019 score with a specificity of 24%, though with a sensitivity of 94%. EMR score showed significantly ($P < 0.05$) higher specificity of 44%.

Table 1. Models Performance evaluated on the training and test data sets for sensitivity, specificity, and positive and negative predictive values with a clinical likelihood cutoff of 5% (for ESC2019) and 20% (for EMR).

	ESC2019 score	EMR score
Training		
AUC	0.88 (0.87-0.9)	0.89 (0.87-0.90)
Sensitivity	97% (95%-98%)	96% (94%-97%)
Specificity	21% (17%-50%)	60% (56%-63%)
PPV	51% (50%-52%)	67% (64%-68%)
NPV	91% (86%-94%)	95% (92%-96%)
Test		
AUC	0.72 (0.67-0.76)	0.79 (0.75-0.83)
Sensitivity	94% (84%-98%)	94% (84%-98%)
Specificity	24% (19%-29%)	44% (39%-50%)
PPV	20% (19%-22%)	26% (24%-28%)
NPV	94% (89%-98%)	97% (92%-99%)

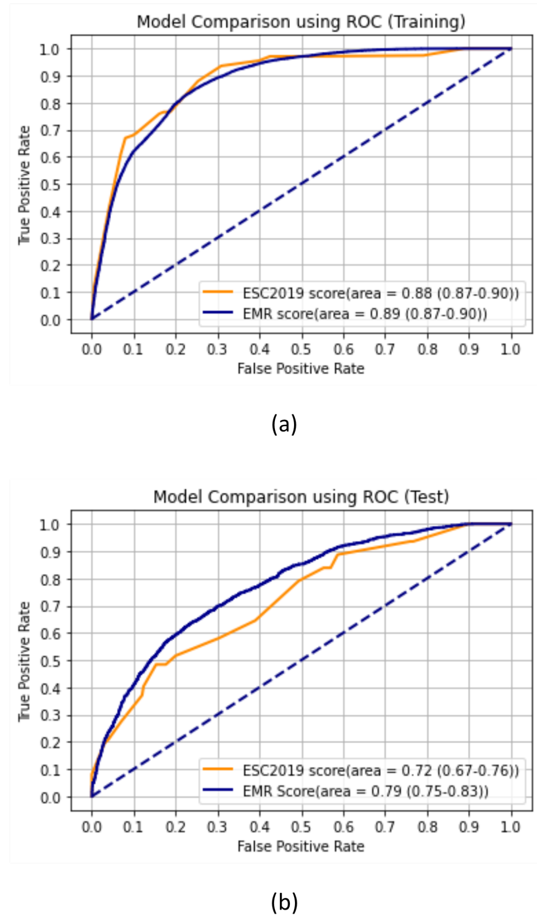

Figure 1. Receiver operating characteristic curve comparison of the ESC2019, and EMR models evaluated on the a) training and b) test data sets.

4. Discussion

Comparing the diagnostic accuracy of the models as evaluated on the test dataset, the results show the low rule-out power of the ESC2019 score with a specificity of 24%, though with a sensitivity of 94%. EMR showed a significantly higher specificity of 44%.

With a sensitivity of 94%, the ESC2019 model exhibits a high ability to identify true positives correctly, however, it has a low specificity of 24%, indicating that it may wrongly identify a significant number of true negatives as positives. As a result, the ESC2019 score may have limited capability for ruling out CAD, which could result in a considerable number of false positive outcomes.

It is important to mention that previous research has shown that the specificity of the ESC2019 score was even lower than the 24% reported in this study. In a study carried out by Winther et al on a group of 15,411 patients, the specificity of the ESC2019 score was reported as 12.1% [6]. Similarly, Larsen reported a specificity of approximately 6% for the ESC2019 score in their study [7].

In contrast, the EMR has a higher specificity of 44%, indicating that it correctly identifies a larger proportion of true negatives, resulting in fewer false positive results. Additionally, EMR has superior positive and negative predictive values, suggesting that it is better at predicting both true positive and true negative results.

The reason for selecting this particular dataset as the test data in this study is its perceived ability to better represent the intended target population. One crucial factor in this decision is the prevalence of CAD within this dataset, which is approximately 17%. It's essential for the test data to closely resemble the target population, including CAD prevalence, because this similarity ensures that the study's results, can be effectively applied to and generalized for the population it intends to inform.

In conclusion, the EMR Score represents a promising advancement in monitoring CAD and risk assessment. Its combination of SCG data and machine learning techniques enhances diagnostic accuracy while prioritizing patient comfort and safety. As further research unfolds and the EMR Score undergoes validation and integration into clinical practice, it holds the potential to significantly impact CAD detection, ultimately benefiting patients and healthcare systems.

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