Article
JOURNAL OF UNIVERSITY OF BABYLON
For Pure and Applied Sciences (JUBPAS)
Vol. 34 ; No. 2| 2026

مجلة جامعة بابل للعلوم الصرفة والتطبيقية مجلة جامعة بابل للعلوم الصرفة والتطبيقية مجلة جامعة بابل للعلوم الصرفة والتطبيقية

ISSN: 2312-8135 | Print ISSN: 1992-0652

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Deep Learning-Based Classification of Reduced Ejection Fraction from Wearable Multimodal Cardiac Signals

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الكشف عن انخفاض نسبة ضخ القلب للدم بطريقة التعلم العميق قائمة على إشارات قلبية مسجلة من أجهزة قابلة للارتداء

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Accepted:	**6/5/2026**			**Published:**	**30/6/2026**

ABSTRACT

Background: Cardiovascular diseases are common among elderly people. Some of these diseases cause reduced ejection fraction (EF), which leads to systolic heart failure. The standard medical procedures to identify low EF are echocardiography and right heart catheterization (RHC). However, these procedures are either not suitable for continuous monitoring or invasive. Utilizing advancements in wearable devices and deep learning models, this work investigates the early detection of low EF using multimodal cardiac signals.

Materials and Methods: In this work, a deep learning algorithm is proposed that ensembles a time-frequency two-dimensional CNN (2D CNN) model and a time-domain one-dimensional Convolutional Neural Network (1D CNN) model to detect low EF. The algorithm uses segments of electrocardiogram (ECG) and seismocardiography (SCG) signals captured by a wearable device placed on the subject's chest. The SCG-RHC dataset was used for training and evaluation of the proposed algorithm. This dataset consists of recorded signals from 73 patients undergoing right heart catheterization.

Results: A standard subject-based five-fold cross-validation approach was used to evaluate the performance of the proposed algorithm. Near-perfect validation performance (accuracy of 99% and F1-score of 99%) was achieved, along with good generalization to unseen subjects.

Conclusion: Despite the limited dataset size, the achieved results demonstrate the potential of using wearable devices combined with the proposed algorithm for the initial screening of low EF. Given its non-invasive nature, remote monitoring of patients with cardiovascular diseases is feasible.

Key words: Artificial Intelligence, CNN, Ensemble Learning, Wearable Sensors, Ejection Fraction.

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INTRODUCTION

Cardiovascular diseases are one of the leading causes of mortality worldwide, accounting for approximately 18.6 million deaths in 2019, and this number continues to increase [1]. Left ventricular ejection fraction (EF) is a key indicator for the diagnosis and management of heart failure [2]. In particular, reduced EF (EF < 40%) is associated with a high risk of systolic dysfunction [3]. Therefore, accurate and timely detection of low EF is essential for the prevention of heart failure and long-term monitoring.

Echocardiography is the standard non-invasive approach for estimating EF in routine clinical practice [2]. In specific clinical scenarios, right heart catheterization (RHC) is performed to provide direct intracardiac pressure measurements and is considered the reference standard due to its direct hemodynamic assessment [4]. On the one hand, echocardiography requires specialized equipment and trained personnel in clinical settings. Its availability is limited, and it is not suitable for continuous or remote monitoring. On the other hand, RHC is invasive and unsuitable for repeated screening. These limitations motivate the development of alternative non-invasive approaches that utilize wearable devices capable of assessing cardiac function outside traditional clinical environments.

Recent advances in wearable sensing technologies have enabled the continuous recording of cardiac mechanical and electrical signals outside clinical settings, such as in homes [5]. These signals include electrocardiography (ECG) and seismocardiography (SCG). ECG provides electrical characteristics of cardiac activity, while SCG captures mechanical vibrations of the heart generated by myocardial contraction, valve opening and closing, and blood ejection [5, 6]. Prior studies have demonstrated that SCG morphology and timing features correlate with mechanical cardiac events, such as the opening and closing of the mitral and aortic valves, enabling the estimation of ventricular performance [7]. The combined utilization of ECG and SCG modalities offers complementary electrical and mechanical cardiac features, which can be used in data-driven cardiac applications based on deep learning approaches.

One of the most used deep learning approaches is convolutional neural networks (CNNs), which have shown strong capability in extracting hierarchical representations directly from biomedical signals such as ECG, EEG, and EMG [8]. CNNs have advantages over traditional machine learning models that require domain knowledge for handcrafted feature extraction. They are data-driven models that learn discriminative patterns for both classification and regression tasks. In cardiovascular applications, CNN-based models have been applied to annotate SCG and ECG fiducial points [9], and to process ECG signals for the detection of cardiovascular diseases such as arrhythmias and coronary artery disease [10]. These applications support their potential for functional cardiac assessment.

This work proposes an ensemble deep learning algorithm based on CNN architectures for the automated detection of reduced EF using ECG and SCG signals. The proposed method combines two models: a time-domain one-dimensional CNN and a time–frequency two-dimensional CNN.

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The remaining sections are organized as follows: the Materials and Methods section describes the utilized dataset and the proposed algorithm; the Results and Discussion section presents the evaluation protocol, detailed results of each model, and discussion; and the final section provides the Conclusion.

MATERIALS AND METHODS

SCG-RHC Dataset

In this work, the Wearable Seismocardiogram Signal and Right Heart Catheter Dataset (SCG-RHC) was used [11, 12]. This dataset consists of recordings of ECG, SCG, and pressure signals collected during right heart catheterization (RHC) procedures carried out in a quiet laboratory setting. The recordings were obtained from 83 patients who were referred for hemodynamic evaluation primarily for heart failure assessment. Their ages ranged between 26 and 84 years, and 49 of them were male.

Before the hemodynamic evaluation, a wearable patch was placed on the subjects’ mid-sternum, along with a separate synchronized multi-lead ECG device. During the evaluation, the catheter was positioned in four locations: right atrium, right ventricle, pulmonary artery, and pulmonary capillary wedge position. These locations were repeated during vasodilator infusion, so there is in total 8 locations or phases. The timing of each placement was recorded and later used to extract 20-second segments in this work. The total number of extracted segments from all subjects was 394. The data of two subjects were excluded due to misalignment in the recorded timings.

The wearable patch recorded single-lead ECG and 3D SCG signals. The three SCG directions were lateral, head-to-foot, and dorsal–ventral. All recorded signals were synchronized, and the sampling frequency was 500 Hz. The pressure signals collected during the invasive evaluation were not used in this work. Additionally, data from the separate ECG device were not used in this study.

Multiple clinical metrics were measured for each phase, including EF percentage. Figure 1 shows the distribution of EF percentage across all segments. The segments were divided into two classes based on EF percentage: EF $< 40\%$ and EF $\geq 40\%$.
In this work, the synchronized ECG and SCG signals were used as model inputs, while the EF-based classes were used as the target labels.

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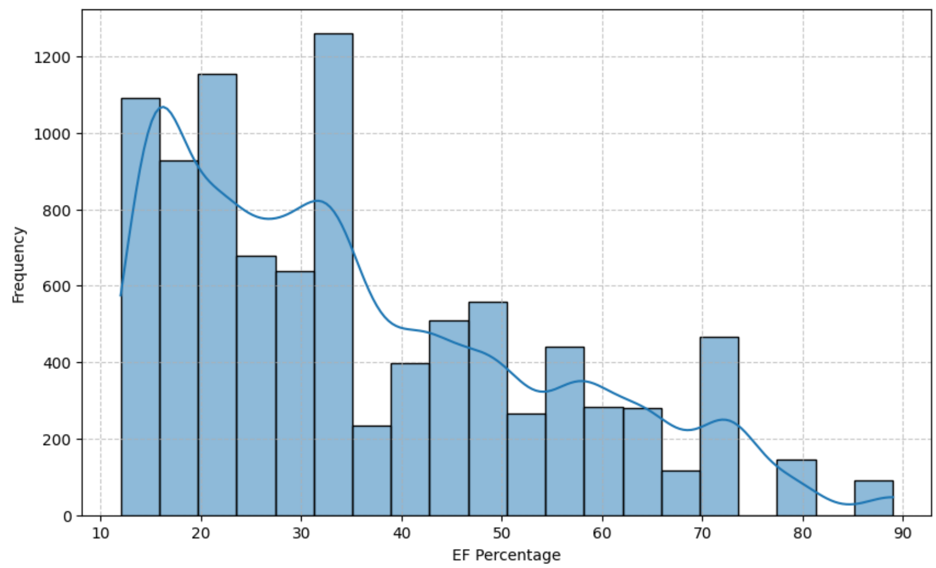

Figure 1 Distribution of EF percentage across all segments extracted from the eight phases.

METHODOLOGY

Figure 2 shows the overall pipeline for the training and evaluation of the proposed deep learning algorithm for the detection of reduced EF. This section first describes the preprocessing of the biomedical signals, second it details the proposed 2D CNN and 1D CNN models, and third it describes the ensemble process.

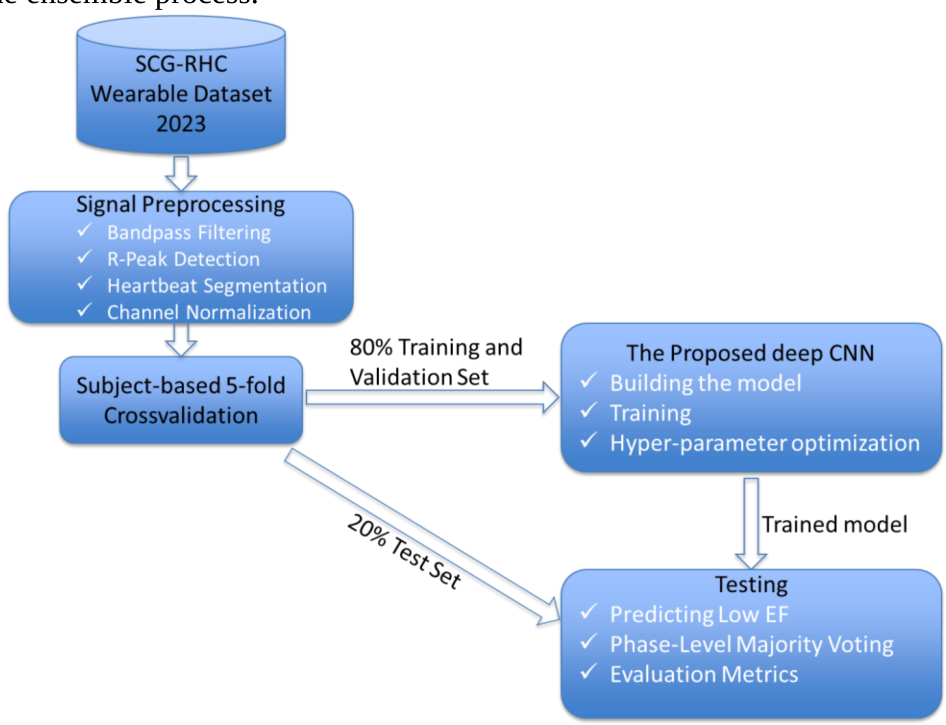

Figure 3 The overall pipeline for the training and evaluation of the proposed deep algorithm.

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The preprocessing procedure has the following steps:

- **ECG and SCG filtering:** To preserve relevant cardiac activities while reducing noise, the ECG and SCG signals were filtered using an n^{th} order Butterworth bandpass filter. The transfer function of this filter is shown in Equation 1, and the filtered signal X(t) is obtained by applying the filter to the input signal Xi(t) using Equation 2.

$$H(s) = \frac{1}{\sqrt{1+\left(\frac{s}{\omega_c}\right)^{2n}}} \quad (1)$$

$$X(t) = Xi(t) * h(t) \quad (2)$$

  Where s is the complex frequency variable in the Laplace domain, ω_c is cutoff angular frequency of the filter, and $h(t)$ the filter impulse response.

  ECG signals are filtered using a bandpass filter of order 5 with a low cutoff frequency of 0.5 Hz to remove baseline drift and a high cutoff frequency of 40 Hz to eliminate high-frequency noise. For SCG signals, three filtering bands are applied. The first band is 0.5–60 Hz to capture the opening of heart valves, the second band is 30–90 Hz to capture the closing of heart valves, and the third band is 0.5–90 Hz to preserve all signals related to mechanical cardiac activities.
- **ECG delineation:** QRS points in ECG signals are delineated using the Discrete Wavelet Transform (DWT) implemented in the NeuroKit2 Python library. The detected fiducial points are used in the next step for segmentation.
- **Segmentation:** The ECG and SCG signals are segmented into windows of length 0.8 seconds to include a single heartbeat. For each 20-second segment, the average heart rate is calculated and then used to crop the boundaries of heartbeat signals, with padding applied if necessary at the end of the segment. Each window starts from the Q point. The total number of windows (w) is 9533, where $w \in \mathbb{R}^{400\times 4}$.
  The mathematical representation of this process is as follows:
  Let the multimodal signal be $X(t) = [ECG(t), SCG_1(t), SCG_2(t), SCG_3(t)]$ where t is the time index. If q_i denotes the detected Q point of the i-th heartbeat, then the segmented window is:

$$W_i = X(t), t \in [q_i, q_i + L] \quad (3)$$

  Where $L = 0.8 \times f_s$ and $f_s = 500\text{Hz}$, thus $W_i \in \mathbb{R}^{L\times C}$ and the total number of windows:

$$W = \{W_1, W_2, \dots, W_N\}, N = 9533 \quad (4)$$

- **Normalization:** Each signal is normalized prior to being used to train or test the deep learning models.

Figure 3 shows the **time-frequency 2D CNN** architecture. The first step is transforming the signals within each window into the time-frequency domain. A Continuous Wavelet Transform (CWT) is applied using complex Morlet wavelets in the PyWavelets library. CWT is suitable for analyzing non-stationary biomedical signals. It is computed across 64 frequency scales corresponding to physical frequencies between 1 Hz and 100 Hz. The CWT coefficients are then

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converted into a wavelet power spectrum by computing the squared magnitude of the coefficients ($|CWT|^2$). The extracted power spectrum is then fed into four blocks of 2D convolutional filters, each followed by a max-pooling layer. After that, a flattened layer is applied, followed by two fully connected layers. Dropout layers with 0.3 rate were used beside L2 regularization. The final layer used softmax activation for binary classification. Adam optimizer with a learning rate of 0.001 and categorical cross-entropy loss were applied (shown in Equation 5).

The total loss used during training becomes:

$$L = -\frac{1}{N}\sum_{i=1}^{N}[y_i \log(\hat{y}_i) + (1 - y_i)\log(1 - \hat{y}_i)] + \lambda \sum_{j=1}^{M} ||W_j||_2^2 \quad (5)$$

Where N is number of training samples, y_i is true label, $\hat{y}_i$ is the predicted probability from the CNN, W_j are weights of layer j, M is the number of layers with trainable weights, and λ is L2 regularization coefficient.

Figure 4 shows the **time-domain 1D CNN** architecture for the detection of low EF. The input to this model consists of ECG and two filtered bands of SCG signals segmented for each heartbeat. The filtering bands are 0.5–60 Hz and 30–90 Hz. The input shape is 400×7, and the CNN architecture is similar to the previously described architecture, except that it uses 1D convolutional filters.

One of the machine learning techniques that is use to improve overall performance is Ensembling. Ensembling is combining the regression or classification results from multiple models by bagging, boosting, or averaging. This technique reduces variance and provides better generalization by combining the strengths of multiple models.

In this work, each of the 2D and 1D CNN models provides a distinctive perspective on the data. Therefore, ensembling both models improves the overall performance. Probability averaging is applied for this purpose. Additionally, the final probability is averaged across the 20-second period to detect low EF. The mathematical representation of this process is as follows:

Let's suppose that both models output a probability of low EF: $p_{1D} = f_{1D}(W_i)$ and $p_{2D} = f_{2D}(W_i)$ where f_{1D}= 1D CNN model and f_{2D}= 2D CNN model, then probability averaging for a 20-second segment that consists of n windows is shown in Equation 6.

$$P_{segment} = \frac{1}{n}\sum_{i=1}^{n}\frac{p_{1D,i} + p_{2D,i}}{2} \quad (6)$$

The final prediction is

$$\hat{y} = \begin{cases} 1 & P_{segment} \geq \tau \\ 0 & P_{segment} < \tau \end{cases} \quad (7)$$

Where τ was fixed to 0.5 in this study.

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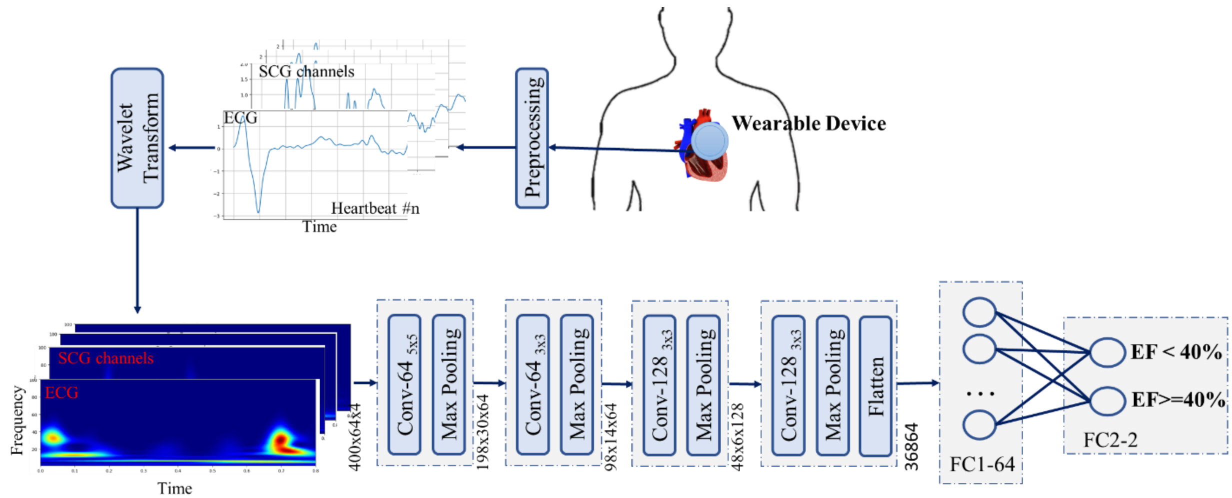

Figure 4 The time-frequency 2D CNN architecture for the detection of low EF. The input to this model is power spectrum of ECG and three SCG signals segmented for each heartbeat. The input shape is 400x64x4. The output is the probability of low EF (i.e. EF<40%).

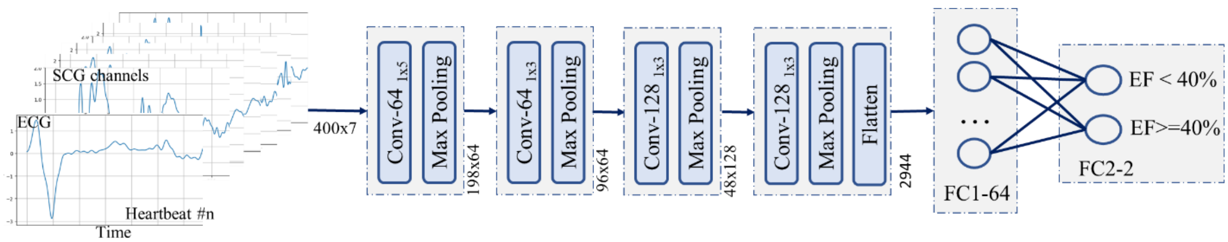

Figure 5 The time-domain 1D CNN architecture for the detection of low EF. The input to this model is ECG and two filtered bands of SCG signals segmented for each heartbeat. The input shape is 400x7 and output shape from each convolutional block is also noted.

RESULTS AND DISCUSSIONS

The training and evaluation of the proposed deep learning algorithm were conducted using a subject-based five-fold cross-validation approach on the SCG-RHC dataset. Each fold contained segments from 16 subjects, except for one fold that contained 17 subjects. In each iteration, four folds were used for training and validation using an 80/20 split, while the remaining fold was used for testing. The performance of the algorithm was evaluated using the following metrics: accuracy, precision, recall, and F1-score.

Each of the 2D CNN and 1D CNN models was trained independently, after which their outputs were combined using the proposed ensemble method. Figure 5 shows the training and validation accuracy and loss curves of the 2D CNN model during the first fold. The curves show smooth convergence and stable training behavior, and similar patterns were observed in the remaining folds. Despite this convergence in Figure 5, we noticed a gap between validation and testing performance that suggests a degree of overfitting. The first reason is that inter-subject variability

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is low between the validation and validation data while it is high between the training and testing data, and the second reason is the limited dataset size.

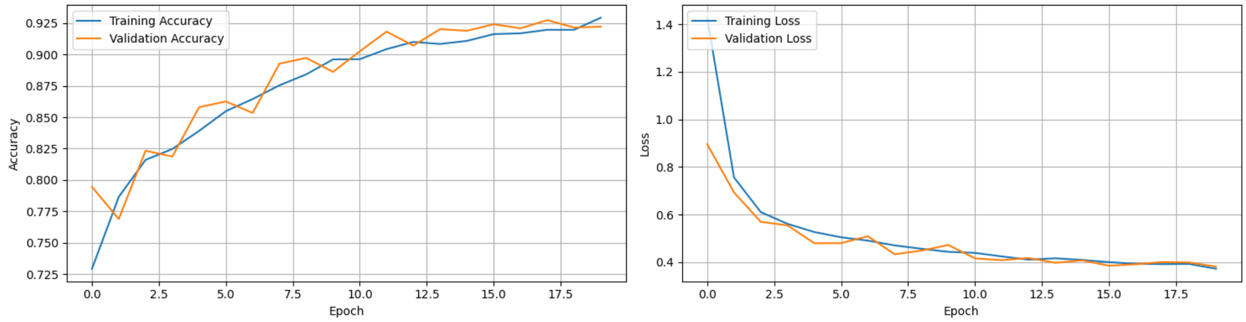

Figure 6 Accuracy and loss curves of training and validation set during fold 1 of the 2D CNN crossvalidation.

The average validation and testing performance across all folds is presented in Table 1 for the three models. All models achieved near-perfect performance on the validation data. However, the proposed ensemble model achieved the highest performance on the test data, with an accuracy of 73.6%, a precision of 0.75, a recall of 0.74, and an F1-score of 0.71. The lower test accuracy compared to the validation accuracy reflects inter-subject variability, which is common in biomedical signal analysis.

Most of the reviewed studies rely on deep learning methods applied to echocardiography images or videos, which remain the clinical standard for cardiac function assessment [13, 14, 15]. For example, Zhang et al. developed a deep learning framework for automated interpretation of echocardiographic images and demonstrated that convolutional neural networks can accurately estimate cardiac function parameters such as EF [15]. Although these approaches achieve high accuracy, they are typically limited to clinical environments and are not suitable for continuous monitoring.

SCG has gained increasing attention as a method for capturing cardiac mechanical activity and enabling wearable cardiac monitoring systems [7]. For example, Shandhi et al. demonstrated that SCG signals combined with machine learning can estimate intracardiac pressure changes in multiple heart positions during right heart catheterization in patients with heart failure [12]. More recently, Lai and Zhang proposed a deep learning framework for identifying fiducial points in SCG signals using sequence labeling techniques [9]. Sandler et al. investigated waveform features in SCG recordings of heart failure patients and reported features that may serve as early indicators of heart-failure readmission [16].

To the best of our knowledge, there is still a limited body of research investigating the use of ECG and SCG signals for detecting reduced EF and related heart failure conditions [17, 18, 19]. For instance, Lin et al. developed a wearable cardiac monitoring system that integrates multi-channel mechanocardiogram (MCG) sensors and ECG signals to estimate the contractility coefficient (CC) [17].They reported a negative correlation between CC and left ventricular

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ejection fraction (LVEF) with a correlation coefficient of −0.73 ($p < 0.001$). Dhar et al. proposed a machine learning approach integrating SCG, ECG, and galvanic skin response (GSR) signals to predict heart failure readmission [18]. Using subject-based cross-validation on 81 patients, their study achieved the best performance with a K-nearest neighbor classifier with an accuracy of 88.9%. In contrast, the proposed approach aims to detect reduced EF before hospitalization, whereas Dhar et al. focused on predicting readmission after the first hospitalization.

Table 1 The validation and testing performance averaged across all the folds of the crossvalidation.

Model	**Validation Performance**				**Testing Performance**			
	Accuracy (%)	**Precision**	**Recall**	**F1-score**	**Accuracy (%)**	**Precision**	**Recall**	**F1-score**
Time-Frequency 2D CNN model	98.98	0.9900	0.9898	0.9898	70.05	0.6974	0.7005	0.6802
Time-domain 1D CNN model	98.48	0.9851	0.9848	0.9847	71.07	0.7090	0.7107	0.6920
The proposed ensemble model	**99.24**	**0.9925**	**0.9924**	**0.9924**	**73.60**	**0.7487**	**0.7360**	**0.7132**

The main limitation of this study is the small dataset size, which includes recordings from 83 subjects mainly due to the difficulty and limited availability of RHC procedures. Despite the limited training data, the proposed method demonstrated promising generalization performance. Collecting additional data in future studies could further improve model performance and enable the development of methods for estimating EF percentage rather than only detecting reduced EF. Moreover, future work may explore advanced transformer-based models and multimodal fusion strategies with domain-specific features to improve the integration of ECG and SCG signals.

Another limitation relates to the quality of the ECG signals. Most subjects suffered from underlying cardiovascular diseases that resulted in abnormal ECG recordings. Data analysis showed that the DWT-based ECG delineation method occasionally missed or mislocalized some heartbeats. Therefore, future work should investigate more robust ECG delineation algorithms during the preprocessing stage to improve the reliability of heartbeat segmentation [20].

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CONCLUSION:

This study presented an end-to-end deep learning framework for the detection of reduced ejection fraction using ECG and SCG signals. The proposed pipeline begins with preprocessing and heartbeat segmentation of the multimodal signals. Two deep learning models are then applied to estimate the probability of reduced EF: a time-domain 1D CNN and a time–frequency 2D CNN. The outputs of both models are combined using a probability-averaging ensemble strategy, and the predictions are aggregated across a 20-second segment to produce the final classification.

Using subject-based cross-validation to evaluate generalization to unseen individuals, the proposed approach achieved a validation accuracy of 99.24% and a testing accuracy of 73.6%. These results demonstrate the feasibility of combining multimodal wearable cardiac signals with deep learning models for the non-invasive detection of reduced EF. The proposed method has the potential to support early screening of cardiac dysfunction and enable future remote monitoring applications using wearable sensing technologies.

Conflict of interests.

The author has no conflict of interest in this work.

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ISSN: 2312-8135 | Print ISSN: 1992-0652

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الخلاصة

المقدمة: تُعد أمراض القلب والأوعية الدموية من أكثر أسباب الوفاة شيوعًا بين كبار السن. بعض هذه الأمراض يؤدي إلى انخفاض نسبة ضخ القلب للدم (Ejection Fraction)، مما قد يسبب فشل القلب الانقباضي. تُستخدم تقنيات مثل تخطيط القلب (Echocardiography) وقسطرة القلب لتشخيص انخفاض نسبة الضخ، إلا أن هذه الطرق إما غير مناسبة للمراقبة المستمرة أو أنها إجراءات جراحية. ومع التطور في الأجهزة القابلة للارتداء وتقنيات التعلم العميق، أصبح من الممكن استكشاف طرق غير جراحية للكشف المبكر عن انخفاض نسبة الضخ باستخدام الإشارات القلبية متعددة الأنماط.

طرق العمل: في هذا العمل تم اقتراح خوارزمية تعتمد على التعلم العميق للكشف عن انخفاض نسبة ضخ القلب للدم باستخدام إشارات تخطيط القلب الكهربائي (ECG) وإشارات الاهتزاز القلبي (SCG) المسجلة بواسطة جهاز قابل للارتداء يوضع على صدر المريض. تتكون الخوارزمية من نموذجين: نموذج شبكة عصبية أحادية البعد (1D CNN) يعمل في البعد الزمني، ونموذج شبكة عصبية ثنائية البعد (2D CNN) يعمل في المجال الزمني–الترددي. تم استخدام قاعدة بيانات SCG–RHC التي تحتوي على إشارات مسجلة من مرضى خضعوا لإجراء قسطرة القلب اليمنى. بعد معالجة الإشارات وتقسيمها إلى نبضات قلبية، يتم تقدير احتمال انخفاض نسبة الضخ باستخدام كلا النموذجين، ثم دمج النتائج باستخدام أسلوب التجميع (Ensemble) للحصول على القرار النهائي.

النتائج: أظهرت نتائج التقييم باستخدام أسلوب التحقق المعتمد على تجزئة البيانات على مستوى المريض أن الخوارزمية المقترحة حققت دقة توقع على بيانات التحقق بلغت 99.24% ودقة توقع على بيانات الاختبار بلغت 73.6%.

الاستنتاجات: على الرغم من قلة البيانات المستخدمة في التدريب, تشير النتائج إلى إمكانية استخدام الإشارات القلبية متعددة الأنماط المسجلة بواسطة الأجهزة القابلة للارتداء مع تقنيات التعلم العميق في الكشف المبكر عن انخفاض نسبة ضخ القلب، مما يفتح المجال لتطبيقات المراقبة القلبية عن بُعد في المستقبل.

الكلمات المفتاحية: الذكاء الاصطناعي، الشبكات العصبية، التعلم العميق، الأجهزة القابلة للارتداء، نسبة ضخ القلب.