A Hybrid CNN-LSTM Model for Heart Failure Detection Using Raw ECG Signals

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Abstract

Heart failure (HF) represents a significant burden on healthcare systems that affects more than 64.3 million people worldwide. Its complications contribute to the annual demise of approximately 7 million people. This complex syndrome encompasses three distinct classes based on left ventricle ejection fraction (LVEF), i.e., preserved (HFpEF), mid-range (HFmEF), and reduced (HFrEF). Early and accurate diagnosis of these subclasses is crucial for optimal management and prognosis. This study focuses on utilizing raw electrocardiogram (ECG) signals, without the need for feature engineering, for the precise detection of HF classes. The latter is achieved by leveraging a deep learning architecture consisting of Convolutional Neural Network (CNN) and Long Short Term Memory (LSTM) layers. The proposed model demonstrated promising results with an overall accuracy of 86%, with accuracy for detecting HFpEF, HFmEF, and HFrEF classes at 89%, 80%, and 84%, respectively. By integrating deep learning techniques with raw ECG data from remote sensing and wearable devices, healthcare providers can achieve early diagnosis and personalized management of HF, ultimately improving patient outcomes and enabling real-time monitoring.

1. Introduction

Heart failure (HF) imposes a significant challenge on healthcare systems affecting more than 64.3 million people worldwide. As the population ages and risk factors like diabetes, hypertension, and obesity become more prevalent, HF has become a primary reason for hospitalizations and deaths on a worldwide scale. Its complications contribute to the annual demise of approximately 7 million people globally [1]. This ailment impacts numerous individuals from various demographic backgrounds, emphasizing the critical necessity for early detection, efficient preventative, therapeutic, and management measures. HF definitions vary across practice guidelines from diverse organizations, i.e., Japanese Heart Failure Society (JHFS) [2], American Society of Echocardiography and the European Association of Cardiovascular Imaging (ASE/EACVI) [3,4]. Despite these variations, strict rules for classification remain challenging due to the multifaceted nature of heart failure etiology, treatment modalities, and the overall clinical manifestation in patients.

In HF assessment, clinicians rely on echocardiography, the gold standard, to stage and assess the risk of progression. Echocardiography primarily focuses on left ventricular ejection fraction (LVEF), a key metric indicating the volume of blood pumped per contraction relative to the chamber's diastolic volume. One complementary, cost-effective, and readily accessible method for continuously assessing HF is electrocardiography (ECG). The capacity of ECG to record important physiological connections indicative of heart function supports the use of this technique for LVEF measurement. Utilizing deep learning methodologies, particularly Convolutional Neural Network (CNN) and Long Short Term Memory (LSTM) architectures, alongside ECG data has shown promising results in diagnosing cardiac conditions, such as congestive HF, Coronary Artery Disease (CAD), and Myocardial Infarction (MI) cases [5,6].

In this paper we propose, a hybrid CNN-LSTM model for HF detection using raw ECG signals collected via wearable and remote sensing devices. By offering a time-saving, cost-efficient, and reliable early diagnostic approach, our model aims to reduce misdiagnosis rates and streamline clinical protocols. This method enhances diagnostic accuracy while minimizing physician workload, maximizing the value of ECG data in HF detection and management.

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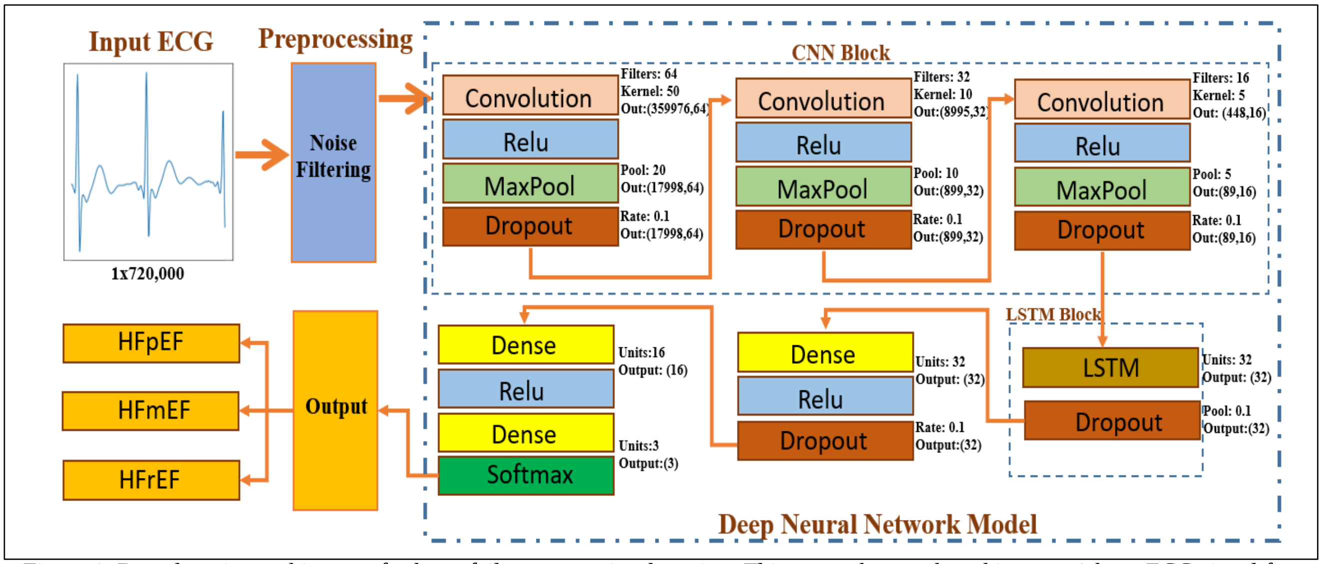

Figure 1. Deep learning architecture for heart failure categories detection. This network starts by taking raw 1-hour ECG signal from a HF patient, then proceeds with the hybrid CNN-LSTM model to end with the HF category (e.g., HFpEF, HFmEF, and HFrEF).

2. Methods

2.1. Dataset

Two sources contributed the data for this study (n = 303 patients); the PRESERVE EF study [7] and the archives of the Intercity Digital Electrocardiography Alliance (IDEAL) study of the University of Rochester Medical Center Telemetric and Holter ECG Warehouse (THEW) [8]. The PRESERVE EF study was approved by the ethics committee at seven participating cardiology departments in Greece and was endorsed by the Hellenic Society of Cardiology, Greece. In contrast, the enrolment protocol of the THEW study was conducted following the Declaration of Helsinki and in accordance with Title 45, U.S. Code of Federal Regulations. Both cohorts provided consent before participating in the studies. All patients were then classified according to the ejection fraction (EF) level following the recommendations of the ASE/EACVI [3,4] as preserved EF (>55%), mid-range EF (between 55% and 50%), and reduced EF (<50%). Thus, the dataset consisted of 129 HF patients with preserved EF (HFpEF), 92 HF with mid-range EF (HFmEF), and 82 HF patients with reduced EF (HFrEF). Using three pseudo-orthogonal lead configurations, all patients in this study recorded their 24-hour Holter ECGs sampled with 200 Hz. We made sure that every recording is set to start from hour 12 AM by applying the Cosinor analysis approach [9].

Based on findings from previous studies [10], we selected the hour from 22:00 to 23:00 as the raw ECG input for our model to detect HF due to its demonstrated superior performance in estimating LVEF levels during this high-risk period for cardiovascular events and physiological stability. The SDROM-ADF filter was used to filter the ECG data for noise [11]. Resulting in a $1 \times 720{,}000$ matrix for each ECG. ECG signals and associated LVEF measurements were split into an 80% training set (242 patients) and 20% (61 patients) testing set.

2.2. Deep Learning model architecture

The proposed model consists of 11 layers as follows, i.e., it starts with three sequential convolutional blocks, each integrating a 1-dimensional convolutional layer aimed at extracting high-level features, coupled with Rectified Linear Unit (ReLU) activation functions to achieve non-linear capabilities. Subsequently, the ReLU layer outputs are directed to max-pooling layers to condense feature dimensions and highlight significant features. The output from the final convolutional block is then passed to LSTM layer, known for its ability to manage long-term dependencies and mitigate issues like exploding gradients, owing to its memory blocks and recursive feedback connections. In order to prevent overfitting, dropout layers are used, which randomly deactivate some nodes during training. Additionally, the architecture includes multiple dense layers that are fully connected and positioned effectively to change the vector dimensions and convert few-dimensional characteristics into linear vectors. Finally, the output vector is processed into probabilities for each class by the final layer, utilizing a softmax activation function for multi-class classification. Figure 1 illustrates a comprehensive architecture of the proposed hybrid CNN-LSTM model. Training and testing were conducted over 100 epochs, and the model parameters were optimized iteratively using a learning rate of 0.1 in the adaptive moment estimation (ADAM) optimizer. Analysis of the prediction confusion matrix, receiver operating characteristic (ROC) curves, and the associated area under

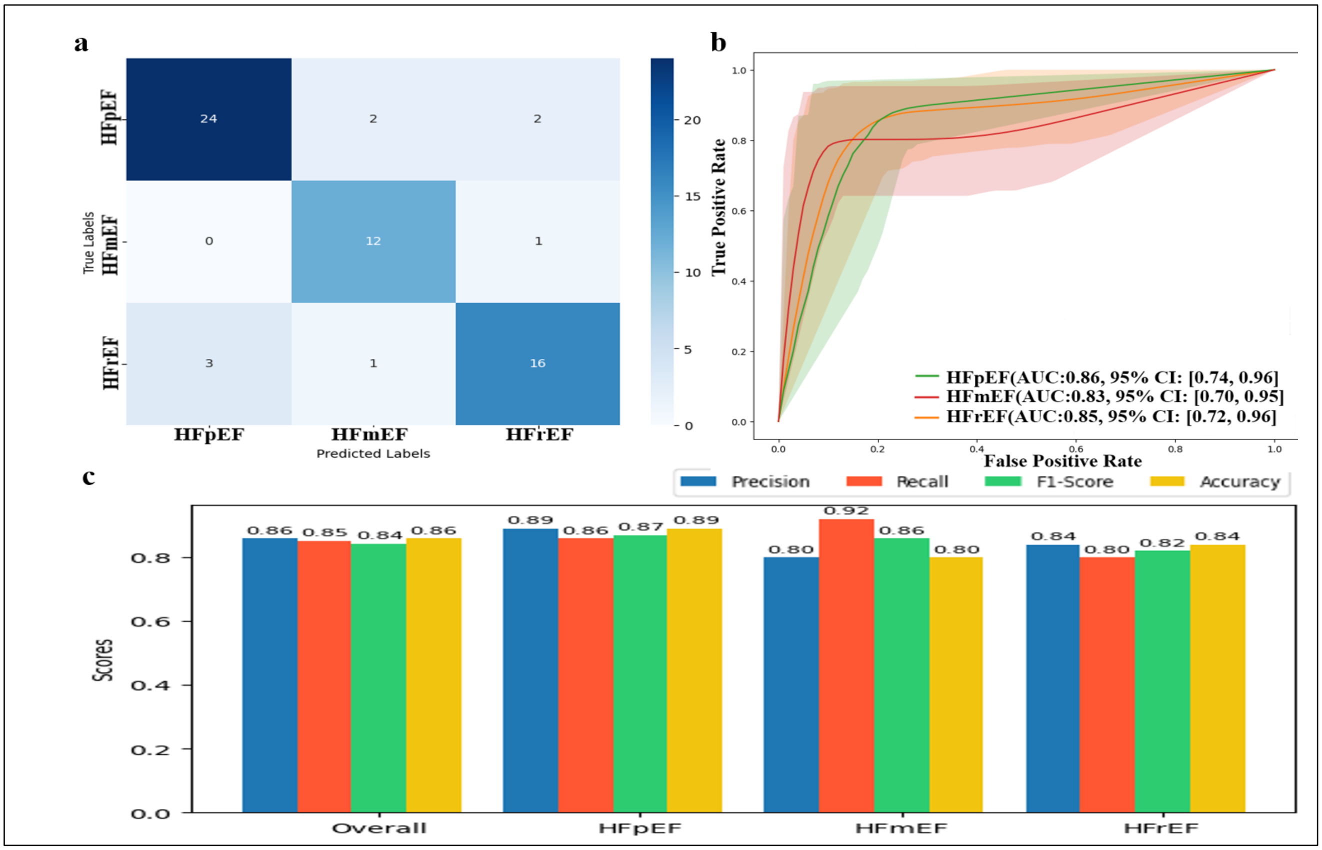

Figure 2. Performance of the proposed CNN-LSTM model. a, The confusion matrix for the predictions of heart failure with preserved ejection fraction (HFpEF), failure with mid-range ejection fraction (HFmEF), and failure with reduced ejection fraction (HFrEF). b, Receiver operating curves (ROC) and area under the ROC (AUC) values for HF categories, the shaded area in represents a 95% confidence interval (CI). c, The performance metrics for precision, recall, F1-score, and accuracy.

the ROC (AUC) were calculated to assess the performance of the classification model. In addition, precision, recall, F1-score, and accuracy were performed.

3. Results

The performance of the trained model is illustrated in Figure 2. From the confusion matrix depicted in Figure 2a, it is evident that 52 out of 61 patients were accurately classified. The model had overall discrimination precision, recall, F1-score, and accuracy of 86%, 85%, 84%, and 86%, respectively. In addition, the most precise and accurate predictions were achieved with the HFpEF stage with 89% followed by HFrEF (84%) and HFmEF (80%). Furthermore, the best recall and F1- score were achieved with HFmEF with 92%, and 86%, respectively, followed by HFpEF (86%, and 87%), and HFrEF (80%, and 82%), respectively (Figure 2c). We further analyzed the performance of the model through the ROC curves (Figure 2b). The highest area under the ROC curve (AUC) was achieved in predicting the HFpEF stage (AUC: 0.86, 95% Confidence Interval: 0.74-0.96). The predictions of the HFrEF yielded an AUC of 0.85 (95% Confidence Interval: 0.72-0.96). Whereas, HFmEF prediction achieved the lowest ROC among the three HF categories (AUC: 0.83, 95% Confidence Interval: 0.70-0.95).

4. Discussion and Conclusions

In this work, we developed a hybrid CNN-LSTM model to predict HF categorized with respect to the LVEF levels by analyzing raw ECG signals. The rationale for employing this model architecture is its potential to accurately capture the temporal and spatial dependencies present in ECG data. PQRST complexes and ST segment deviations are two examples of localized patterns in ECG signals that CNNs are good at detecting because of their exceptional ability to extract hierarchical spatial features from raw data. However, because LSTMs are good at capturing temporal dynamics and sequential dependencies, the model can identify minute changes in the morphology of the ECG waveform over time that may be signs of underlying cardiac problems [12,13].

Furthermore, the model's detection of physiological and electrical characteristics is essential for distinguishing between the three HF classes. For instance, variations in the amplitude, duration, and morphology of ECG waveforms, such as T-wave inversion, elevation or depression of the ST segment, and broadening of the QRS complex, indicate changes in cardiac function and myocardial conductivity linked to the advancement of HF. These slight variations in ECG features correlate with changes in EF, a critical measure of heart contractility and function [10]. To the best of our knowledge, the current study is an innovation in predicting HF using only raw ECG data, independent of clinical data or the extraction of features such as heart rate variability (HRV) parameters from 24-hour Holter analysis, as compared to recent investigations [10,14-15].

The findings of this study has considerable potential of utilizing deep learning techniques, the developed model offers a non-invasive, cost-effective, and easily accessible approach for HF stage prediction, especially considering the increasing popularity of wearable devices being used for continuous ECG monitoring, eliminating the need for expensive diagnostic tools, complex data extraction processes, or extensive patient clinical information. This accessibility is especially vital for healthcare settings with limited resources, facilitating timely interventions and tailored treatment strategies. Moreover, it highlights how crucial early detection is, particularly for the midrange HF stage, which may advance to HFpEF or HFrEF or change between these subtypes. Notably, studies indicate that individuals with HFmrEF might gain more from HFrEF-related targeted therapy than those with HFpEF [16]. This emphasizes how important it is to have precise and easily available diagnostic tools.

Future studies may explore explainable deep learning within this CNN-LSTM to better understand the extracted features from ECG data. Additional studies could investigate other HF ranges based on different LVEF guidelines. Moreover, it would be valuable to explore the performance of the model across different window sizes of ECG lengths, extending beyond hour-based detection.

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