RESEARCH PAPER

Feature Selection Techniques for ECG-Based CHF Detection: A Systematic Survey

Lumbini Bhaumik[1,2], Abhishek Bandapadhyay[2], Kasturi Barik[1]
[1] JIS Institute of Advanced Studies and Research (JISIASR), JIS University
[2] Asansol Engineering College, Asansol

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ABSTRACT
Congestive heart failure (CHF) is a major cardiovascular condition requiring early and accurate diagnosis. Electrocardiogram (ECG)-based automated detection systems have gained significant attention due to their non-invasive nature and clinical relevance. The performance of such systems largely depends on effective feature engineering and feature selection strategies. This paper presents a systematic survey of feature extraction and feature selection techniques used in ECG-based binary CHF detection. The study reviews time-domain, frequency-domain, time-frequency, and nonlinear feature representations, along with filter, wrapper, and embedded feature selection approaches. Additionally, commonly used ECG datasets, validation protocols, and classification models are critically analyzed. The survey identifies key challenges in existing research, including data imbalance, lack of subject-wise validation, and limited analysis of feature subset robustness. Furthermore, the lack of systematic comparison of feature selection methodologies under unified experimental settings is highlighted. The findings provide a structured understanding of current methodologies and outline important research directions for developing reliable ECG-based diagnostic systems.
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I. Introduction

Cardiovascular diseases remain the leading cause of mortality worldwide, with congestive heart failure (CHF) representing a severe clinical condition characterized by impaired cardiac function. Early detection is essential for improving patient outcomes and reducing mortality rates.

Electrocardiography (ECG) is a widely used non-invasive diagnostic tool for monitoring cardiac activity. With the availability of publicly accessible ECG datasets, machine learning-based automated detection systems have gained significant attention. Traditional approaches rely on handcrafted feature extraction followed by classifiers such as Support Vector Machines (SVM), Artificial Neural Networks (ANN), and Random Forests (RF). More recently, deep learning techniques have also been explored for ECG analysis.

Despite these advancements, several challenges remain. Many studies employ beat-wise validation, which can introduce data leakage and lead to overly optimistic results. Furthermore, feature selection methods are often evaluated using a single classifier, and the consistency of selected features across different validation settings is rarely analyzed.

This paper presents a comprehensive survey of feature selection techniques used in ECG-based CHF detection and identifies key research gaps that need to be addressed. These challenges highlight the importance of robust and systematic feature selection strategies in ECG-based CHF detection.

II. Literature Review

Numerous studies have explored automated CHF detection using ECG signals through different feature extraction and classification techniques. Early approaches relied on handcrafted features combined with traditional classifiers.

Liao *et al.* [1] utilized unit pattern features with SVM, while Masetic and Subasi [2] employed autoregressive coefficients with Random Forest classifiers. Wavelet-based feature extraction has also been widely used, as demonstrated by Sudarshan *et al.* [3], who combined wavelet features with machine learning classifiers.

Hybrid feature extraction approaches were later introduced. Isler *et al.* [4] combined heart rate variability, wavelet, and nonlinear features within a multi-stage classification framework. Similarly, Tripathy *et al.* [5] used entropy-based features derived from Stockwell transform for CHF detection.

Deep learning approaches have further advanced the field. Porumb *et al.* [6] applied convolutional neural networks (CNNs) to raw ECG signals, achieving high accuracy. Nahak *et al.* [7] also demonstrated strong performance using unit pattern features with SVM.

Despite these advancements, limitations remain. Many studies rely on small datasets, high-dimensional feature sets, and complex processing pipelines. Deep learning models may suffer from overfitting and often lack interpretability. Moreover, feature selection is often restricted to a single method, and systematic comparison across different approaches is lacking. A comparative summary of representative studies is presented in Table I.

TABLE I

Summary of Existing Studies

Author	**Method**	**Dataset**	**Accuracy**	**Limitation**
Liao et al.	SVM + unit patterns	NSRDB, BIDMC	97.27%	Small dataset
Masetic et al.	RF + AR features	CHF dataset	99.75%	Limited validation
Sudarshan et al.	Wavelet + ML	MIT-BIH	99.86%	Requires R-peak detection
Isler et al.	Hybrid features	Multiple datasets	98.80%	High complexity
Tripathy et al.	Entropy features	CHF datasets	98.78%	No inter-patient validation
Porumb et al.	CNN	BIDMC	100%	Overfitting risk
Nahak et al.	SVM + unit patterns	NSRDB	99.96%	Limited generalization

III. Feature Engineering in ECG

Feature engineering plays a critical role in ECG-based CHF detection. Features are extracted from multiple domains, including time-domain, frequency-domain, time-frequency, and nonlinear representations.

Time-domain features are simple and computationally efficient but may not capture complex signal variations. Frequency-domain features provide spectral insights but assume stationarity. Time-frequency approaches offer better localization, while nonlinear features capture dynamic behavior.

Although combining multiple feature types improves performance, it increases dimensionality, necessitating effective feature selection. The general workflow of ECG-based CHF detection is illustrated in Fig. 1.

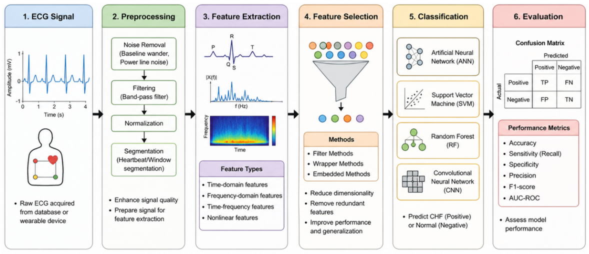

Fig. 1. General pipeline of ECG-based CHF detection system.

IV. Feature Selection Techniques

Feature selection techniques are broadly categorized into filter, wrapper, and embedded methods. Filter methods rely on statistical measures and are computationally efficient but ignore feature interactions. Wrapper methods evaluate feature subsets using classifiers and generally provide better performance, although at higher computational cost. Embedded methods integrate feature selection within model training, offering a balance between performance and efficiency.

Despite extensive research, comparative evaluation of these methods under consistent conditions remains limited. Additionally, the relationship between feature dimensionality and classification performance is not well understood. A comparison of different feature selection approaches is shown in Table II.

TABLE II

Comparison of Feature Selection Methods

Method Type	**Advantages**	**Limitations**
Filter	Fast, scalable	Ignores feature interaction
Wrapper	High accuracy	Computationally expensive
Embedded	Balanced approach	Model-dependent

V. Dataset and Evaluation Challenges

Public ECG datasets such as MIT-BIH NSR and BIDMC CHF are widely used in research. However, these datasets often contain limited samples, which may lead to overfitting.

Many studies use beat-wise validation, resulting in data leakage and inflated performance. Lack of standardized evaluation protocols further complicates comparison across studies. Proper validation should include subject-wise splitting and statistical testing.

VI. Observations and Research Gaps

The literature reveals several important challenges. There is a lack of consistent evaluation across different classifiers and validation settings. Feature selection methods are often evaluated independently, without systematic comparison. Additionally, identifying minimal yet highly informative feature subsets remains an open problem.

These gaps highlight the need for more structured and comparative studies in this domain.

VII. Discussion

Although significant progress has been made, challenges related to generalization, reproducibility, and interpretability remain. Many studies focus on accuracy without considering robustness. Addressing these issues is essential for developing clinically reliable systems.

VIII. Future Research Directions

Future research should focus on systematic evaluation of feature selection methods under unified experimental conditions. Identifying minimal feature subsets while maintaining performance is also important. Furthermore, improving generalization across datasets and enhancing model interpretability are key research directions.

IX. Conclusion

This survey presented a comprehensive review of feature selection techniques for ECG-based CHF detection. Key challenges such as dataset limitations, lack of standardized evaluation, and absence of systematic comparison were identified. Addressing these challenges is essential for developing robust and clinically applicable diagnostic systems.

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