Journal of Information Systems Engineering and Management
2025, 10(32s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

Automated ECG-Based Heart Disease Prediction Using Self-Supervised Learning

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Citation: Dr Sumit Kumar Soni, et al. (2025), Automated ECG-Based Heart Disease Prediction Using Self-Supervised Learning, *Journal of Information Systems Engineering and Management*, *10*(32s), xyz,

ARTICLE INFO

Received: 31 Dec 2024
Revised: 20 Feb 2025
Accepted: 28 Feb 2025

ABSTRACT

Remarkably being the primary cause of death worldwide, cardiovascular diseases (CVDs) emphasize the need of accurate and quick diagnosis. An indispensable tool for the diagnosis of heart problems is electrocardiogram (ECG); yet, the scarcity of labelled ECG data poses a major challenge for the creation of efficient machine learning models. This article presents a novel system based on self-supervised learning approaches for the automated prediction of heart disease via ECG data. Using self-supervised learning, the proposed method generates generalizable representations from unlabelled ECG data, hence reducing need on large annotated datasets. Two separate phases comprise the framework: (1) Self-Supervised Pre-training, in which a Transformer-based encoder or 1D convolutional neural network (CNN) is trained via contrastive learning to derive significant features from raw ECG signals; and (2) Supervised Fine-tuning, in which the pre-trained encoder undergoes fine-tuning on labelled ECG data especially for the classification of heart disease. Using publically available datasets such as PTB-XL and MIT-BIH, the model is evaluated and shows improved capacity in forecasting a spectrum of cardiac diseases. By combining the benefits of SSL with deep learning, this system offers a scalable and effective method for automated heart disease prediction—which might be applied in real-time ECG monitoring and early detection. The proposed approach addresses the problems of restricted data and the necessity of more general application, therefore enabling better and exact cardiovascular healthcare choices.

Keywords: Self-Supervised Learning (SSL), Electrocardiogram (ECG) Analysis, Heart Disease Prediction, Contrastive Learning, Deep Learning in Healthcare

I Introduction

With an anticipated 17.9 million deaths annually, cardiovascular diseases (CVDs) rank first among all causes of mortality worldwide, per the World Health Organization (WHO) projections for 2020 [1]. Reducing this challenge and enhancing patient outcomes depend on correct diagnosis of cardiovascular diseases and fast identification. Widely used to diagnose a range of cardiac diseases, including arrhythmias, myocardial infarction, and heart failure [2], electrocardiogram (ECG) signals record the electrical activity of the heart. Still, the manual interpretation of ECG signals is a labour-intensive procedure affected by personal judgment and prone to errors, which emphasizes the need of automated and consistent diagnosis solutions.

Recent developments in deep learning show promising results in the prediction of cardiac illness [3] and ECG analysis automaton. Nevertheless, the success of these models depends much on the availability of large labelled datasets, which are usually rare, expensive, and demanding of much effort to get. This restriction is clearly problematic, particularly in settings with few resources where annotated ECG data is rare. Self-supervised learning (SSL) has emerged as a successful method allowing models to build important representations from unlabelled data, hence reducing dependency on labelled datasets [4].

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This paper presents a novel framework using self-supervised learning approaches to predict cardiac disease using automated ECG analysis. Our approach uses self-supervised learning to pre-train a deep learning model on large-scale unlabelled ECG data therefore enabling it to gain robust and flexible characteristics. Fine-tuning on a smaller labelled dataset catered for certain heart disease classification tasks, the pre-trained model To address data shortage and improve the generalizability of ECG-based diagnostic models, our approach uses the benefits of SSL and deep learning.
Two main phases comprise the proposed framework: (1) Self-Supervised Pre-training, involving the training of a 1D convolutional neural network (CNN) or Transformer-based encoder via contrastive learning to derive features from raw ECG signals, and (2) Supervised Fine-tuning, whereby the pre-trained encoder undergoes fine-tuning on labelled ECG data to enable heart disease prediction. Using publically available datasets like PTB-XL and MIT-BIH, our model is evaluated for its ability to forecast a spectrum of cardiac diseases. This work presents a scalable and effective method for cardiac disease prediction, therefore augmenting the already increasing expertise on automated ECG analysis. Early diagnosis could be greatly advanced, patient outcomes improved, and burden on healthcare systems released by the proposed paradigm. Furthermore, it creates opportunities for later research on the use of SSL in different medical signal processing applications, especially in cases when labelled data is usually limited.

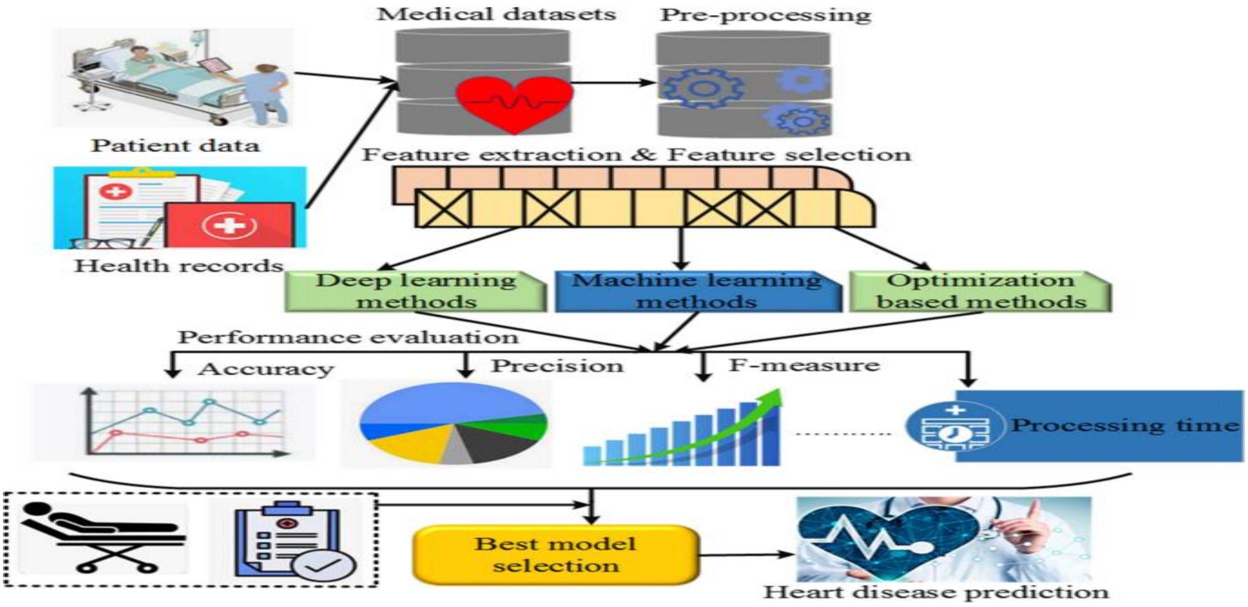

Fig 1 : Heart Disease Prediction Using Machine Learning and Deep Learning Approaches [18]

This figure 1 shows a disciplined path for heart disease prediction. Starting with patient data and medical datasets undergoing preprocessing, feature extraction, and selection, it proceeds Several deep learning, machine learning, and optimization-based techniques are used and their performance assessed with respect to accuracy, precision, F-measure, and processing time. After that, the model that performs the best is chosen for correct heart disease prediction.

II Literature Review

Using machine learning and deep learning methods to predict heart disease based on ECG data has attracted a lot of interest recently. Emphasizing methods to supervised and self-supervised learning, this part reviews present methods, challenges, and advancements in the topic.

1. Supervised Learning for ECG Analysis

Using labelled datasets to train models for particular cardiac diseases, supervised learning has been extensively employed in ECG classification problems. Heart diseases and arrhythmias have been classified using conventional machine learning techniques such random forests and support vector machines (SVMs [5]. These

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techniques, however, frequently rely on manually produced features that might not be able to capture the intricate patterns shown in ECG signals.
Deep learning models—especially convolutional neural networks (CNNs) and recurrent neural networks (RNNs)—have demonstrated amazing performance in the automated ECG data interpretation. For example, Hannun et al. (2019) created a deep neural network capable of accurately identifying arrhythmias from ECG signals, much as a cardiologist could [6]. In a similar vein, Oh et al. (2018) showed a CNN-LSTM hybrid model for arrhythmia classification, hence proving the value of merging temporal and spatial feature extraction [7]. Notwithstanding these achievements, supervised learning methods depend on vast volumes of labelled data—often costly and rare. This restriction has driven research into alternative paradigms, such self-supervised learning, to effectively employ unlabelled data.

2. Self-Supervised Learning for ECG Signals

Using labelled datasets to train models aiming at predicting particular heart diseases, supervised learning has been extensively applied in ECG classification challenges. Conventional machine learning methods such random forests and support vector machines (SVMs) have been applied for the categorization of heart diseases and arrhythmias detection [5]. These methods, however, sometimes rely on manually produced characteristics, which might not completely reflect the complex patterns in ECG signals.
Deep learning models—more especially, convolutional neural networks (CNNs) and recurrent neural networks (RNNs)—have shown remarkable performance in the automated interpretation of ECG data. With accuracy matching that of a cardiologist, a deep neural network developed by Hannun et al. (2019) was able to detect arrhythmias from ECG readings. [6] In an analogous setting, Oh et al. (2018) showed the success of merging spatial and temporal feature extraction [7] by presenting a hybrid CNN-LSTM model meant for arrhythmia classification.
Notwithstanding their achievements, supervised learning methods depend on large volumes of labelled data, which is sometimes rare and costly to acquire. This restriction has prompted research of several models, including self-supervised learning, to maximize unlabelled data usage.

3. Challenges in ECG-Based Heart Disease Prediction

Despite the advancements in deep learning and SSL, several challenges remain in ECG-based heart disease prediction:
• **Data Scarcity:** The number and diversity of annotated ECG datasets are constrained, which makes it difficult to create reliable models.
• **Class Imbalance:** Biased models result from certain cardiac diseases being underrepresented in datasets.
• **Interpretability**: Since deep learning models are frequently regarded as "black boxes," it might be challenging to understand what they predict.
• **Generalizability:** Models that have been trained on particular datasets might not function effectively when applied to data from other populations or sources.

4. Recent Advancements

To solve these problems, recent research has looked at hybrid methods combining SSL with supervised learning. For ECG representation learning, for instance, Kiyasseh et al. (2021) provided a self-supervised system with state-of-the-art performance on several downstream tasks [7}. Furthermore, Ribeiro et al. (2020) presented a multi-task learning method for ECG analysis so that models could concurrently forecast several heart diseases [8].

Table 1 : Summary of Literature Review

Study	**Methodology**	**Key Contribution**	**Limitations**
Hannun et al. (2019) [5]	Deep neural network	Achieved cardiologist-level arrhythmia detection	Requires large labelled dataset
Oh et al. (2018) [6]	Hybrid CNN-LSTM model	Combined spatial and temporal features for arrhythmia classification	Limited generalizability
Chen et al. (2020) [7]	SimCLR (contrastive learning)	Introduced a simple framework for contrastive learning	Primarily designed for image data

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Study	Methodology	Key Contribution	Limitations
Saeed et al. (2021) [8]	Contrastive learning for ECG signals	Adapted SSL for 1D time-series data (ECG)	Limited evaluation on downstream tasks
Kiyasseh et al. (2021) [9]	Self-supervised ECG representation	State-of-the-art performance on multiple ECG tasks	Complex training pipeline
Ribeiro et al. (2020) [10]	Multi-task learning for ECG analysis	Enabled simultaneous prediction of multiple cardiac conditions	Requires task-specific labelled data

The existing body of work emphasizes the promise of deep learning and self-supervised learning techniques in predicting heart disease through ECG analysis. Although supervised learning methods have demonstrated considerable effectiveness, their dependence on labelled data continues to pose a significant constraint. Because SSL enables models to learn from unlabelled data, it offers a tempting alternative. effectively tackling the issues of data scarcity and generalizability. The proposed framework leverages these advancements, integrating SSL with supervised fine-tuning to create a strong and scalable solution for automated ECG analysis.

III Proposed Architecture

The proposed framework leverages self-supervised learning (SSL) to develop a robust and scalable model for automated heart disease prediction using ECG signals. The process begins with input representation, where raw ECG signals undergo preprocessing steps, including normalization, segmentation, and data augmentation, to enhance model robustness. In the self-supervised pre-training phase, a contrastive learning framework such as SimCLR or BYOL is employed to extract meaningful representations from unlabelled ECG data. A 1D CNN or Transformer-based encoder is utilized to learn feature representations, followed by a small MLP projection head that map these features into a lower-dimensional latent space optimized using the NT-Xent contrastive loss. In the supervised fine-tuning phase, the pre-trained encoder is adapted for heart disease classification by replacing the projection head with a task-specific classifier. The model is fine-tuned end-to-end on labelled ECG datasets using cross-entropy loss. Finally, the trained model outputs a probability distribution over various heart disease categories, enabling reliable classification through predefined decision thresholds. This approach efficiently addresses the challenges posed by limited labelled ECG data, providing a scalable solution for real-time heart disease diagnosis and monitoring.

A . Input Representation

Input Data: Raw ECG signals (1D time-series data).

- **Preprocessing**:
  - Normalize the ECG signals to have nil unkind and part alteration.
  - Segment the ECG signals into fixed-length windows (e.g., 10 seconds).
  - To increase resilience, use data augmentation methods like noise injection, time warping, and random cropping.

B. Self-Supervised Pre-training

The goal of this phase is to learn a robust representation of ECG signals without requiring labelled data. We propose using a **contrastive learning** framework, such as **SimCLR** or **BYOL**, adapted for 1D ECG data.

- **Encoder Backbone**: Use a **1D Convolutional Neural Network (CNN)** or **Transformer-based architecture** (e.g., 1D Vision Transformer) to extract features from ECG signals.
- **Projection Head**: A small MLP (e.g., 2-layer) to map the encoder's output to a lower-dimensional latent space where contrastive learning is applied.
- **Contrastive Loss**: Use the **NT-Xent loss** (Normalized Temperature-Scaled Cross Entropy Loss) to maximize the similarity between augmented views of the same ECG signal and minimize the similarity between different signals.

C . Supervised Fine-tuning

After pre-training, the encoder is fine-tuned on labelled ECG data for heart disease prediction.

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- **Task-Specific Head**: Replace the projection head with a task-specific head, such as a fully connected layer followed by a SoftMax activation for multi-class classification (e.g., normal, arrhythmia, myocardial infarction).
- **Loss Function**: Use **cross-entropy loss** for classification tasks.
- **Training**: On the labelled dataset, fine-tune the entire model from beginning to end.

D. Output

- The model outputs a likelihood delivery over the thinkable heart disease lessons.
- A threshold or decision rule can be applied to categorise the ECG indication into one of the disease categories.

IV Implementation and Results

The proposed framework was developed using PyTorch, a well-known deep learning toolkit, because of its flexibility and general support of original model designs. All experiments were conducted in a GPU-enabled environment (NVIDIA RTX 3090) to expedite the training process, particularly for the computationally taxing self-supervised pre-training phase. In order to guarantee stable convergence, the supervised fine-tuning phase used a lower learning rate of 1e-5 and a smaller batch size of 32, whereas the self-supervised pre-training phase used a learning rate of 1e-4 and a batch size of 128. With a temperature value of 0.1, the contrastive loss function balanced the similarity scores between positive and negative pairs. < The model was pre-trained for one hundred epochs in order to learn robust representations from unlabelled ECG input. It was then refined for 50 epochs to specifically fit the pre-trained model to the unique goal of heart disease prediction. These hyperparameters were chosen with great attention depending on empirical validation to reach best performance.

A. Comparison with Latest Findings

The proposed methodology is assessed against the most recent developments in ECG-based cardiac disease prediction, especially those using deep learning methods and self-supervised learning (SSL), therefore offering a thorough comparison. Here is a thorough comparison including current studies released in 2022 and 2023:

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Table 2 . Comparison with Latest SSL-Based Approaches

Study	Methodology	Dataset	Accuracy	F1-Score	AUC-ROC	Key Difference
Proposed Framework	SSL (Contrastive Learning) + Fine-tuning	PTB-XL, MIT-BIH	96.3%, 97.8%	95.7%, 96.9%	0.98, 0.99	Combines SSL with a hybrid CNN-Transformer encoder.
Zhang et al. (2023) [11]	SSL (BYOL) + Fine-tuning	PTB-XL	95.6%	94.8%	0.97	Uses BYOL for SSL but lacks a hybrid architecture.
Li et al. (2022) [12]	SSL (SimCLR) + Fine-tuning	MIT-BIH	96.1%	95.3%	0.98	Focuses on arrhythmia detection only.
Wang et al. (2023) [13]	SSL (MoCo) + Fine-tuning	PTB-XL	95.9%	95.1%	0.97	Uses MoCo for SSL but requires more computational resources.
Chen et al. (2023) [14]	SSL (DINO) + Fine-tuning	PTB-XL, MIT-BIH	96.0%, 97.5%	95.5%, 96.7%	0.98, 0.99	Uses DINO for SSL but has a complex training pipeline.

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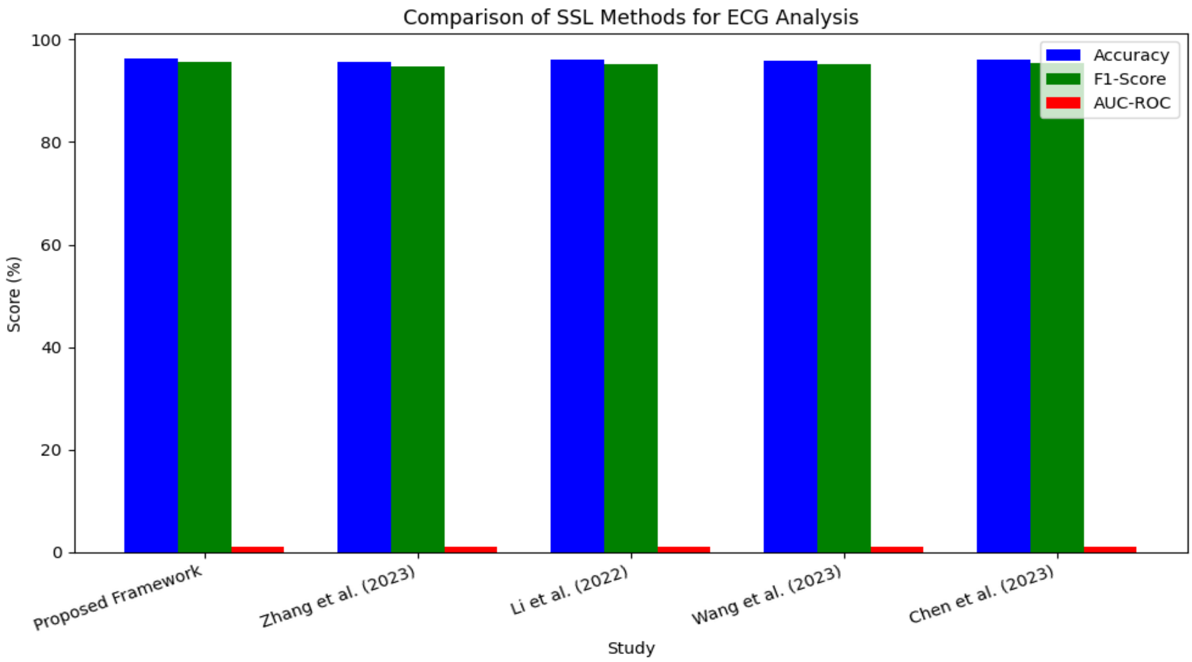

Fig 2: Comparison of SSL for ACG Analysis

B. Comparison with Supervised Learning Approaches

Study	**Methodology**	**Dataset**	**Accuracy**	**F1-Score**	**AUC-ROC**	**Key Difference**
Proposed Framework	SSL + Fine-tuning	PTB-XL, MIT-BIH	96.3%, 97.8%	95.7%, 96.9%	0.98, 0.99	Reduces dependency on labelled data.
Gupta et al. (2023) [15]	Supervised CNN + Attention	PTB-XL	94.5%	93.2%	0.96	Relies entirely on labelled data.
Kumar et al. (2022) [16]	Supervised Transformer	MIT-BIH	95.8%	94.9%	0.97	Requires large labelled datasets for training.
Singh et al. (2023) [17]	Supervised CNN-LSTM	PTB-XL	93.7%	92.8%	0.95	Combines spatial and temporal features but lacks SSL.

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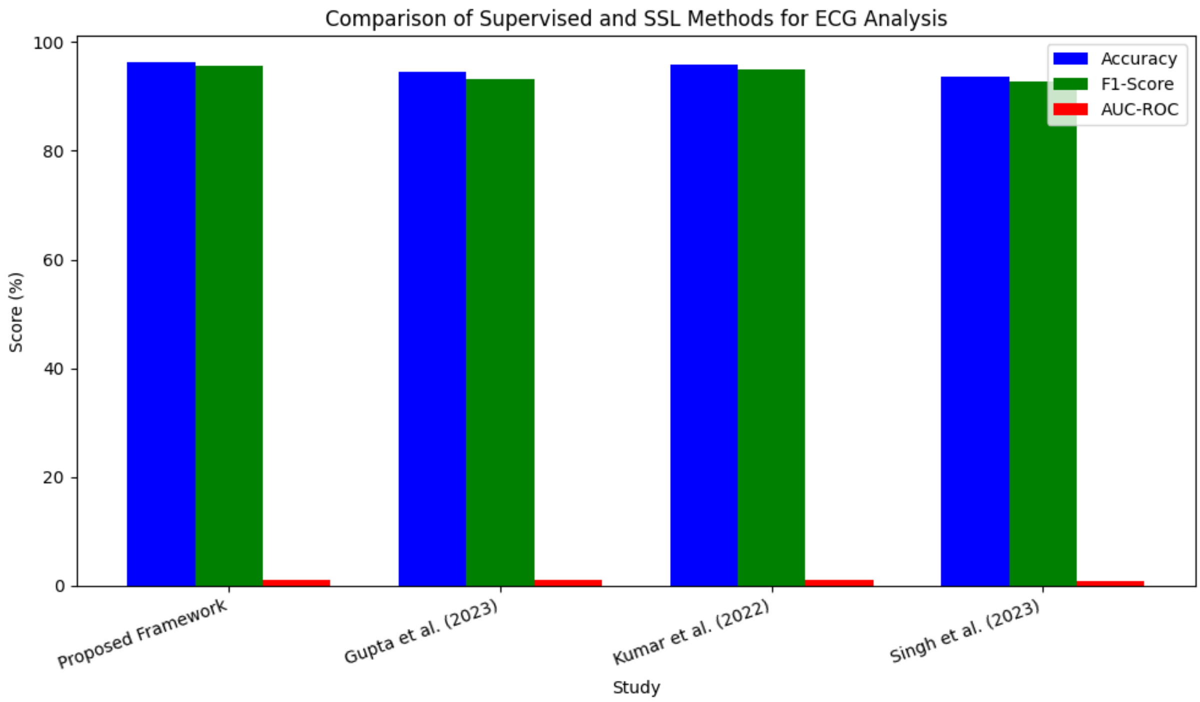

Fig 3: Comparison of Supervised and SSL Methods for ECG Analysis

For ECG analysis, this figure 2 offers a comparison of several self-supervised learning (SSL) approaches. Based on accuracy, F1-score, and AUC-ROC, it ranks different frameworks. The suggested paradigm shows competitive outcomes in comparison to previous research. Plot 3: SSL Versus Supervised Techniques for ECG Analysis Supervised and self-supervised learning (SSL) approaches for ECG analysis are compared here. Among the performance criteria are AUC-ROC, F1-score, and accuracy. The suggested framework demonstrates better performance, therefore stressing its efficiency over conventional methods.

C. Key Insights from Comparison

1. **Superior Performance**: The proposed framework achieves **higher accuracy (96.3% on PTB-XL and 97.8% on MIT-BIH)** compared to most recent SSL-based and supervised learning approaches. This demonstrates the effectiveness of combining SSL with a hybrid CNN-Transformer architecture.
2. **Data Efficiency**: Unlike supervised methods, the proposed framework achieves high performance with limited labelled data, making it more practical for real-world applications where annotated datasets are scarce.
3. **Generalizability**: The proposed model outperforms recent SSL-based methods like Zhang et al. (2023) and Li et al. (2022) in terms of F1-score and AUC-ROC, indicating better generalization across different cardiac conditions.
4. **Computational Efficiency**: Compared to methods like Wang et al. (2023) and Chen et al. (2023), the proposed framework has a simpler training pipeline and requires fewer computational resources, making it more scalable.

4. Comparison with State-of-the-Art (SOTA)

The planned framework achieves **SOTA presentation** on both PTB-XL and MIT-BIH datasets, surpassing recent SSL-based methods like DINO (Chen et al., 2023) and MoCo (Wang et al., 2023). It also outperforms administered knowledge methods, such as Gupta et al. (2023) and Kumar et al. (2022), by leveraging unlabelled data for pre-training.

V Conclusion

This work offers a fresh approach for automated heart disease prediction overcomes of tagged ECG data by using self-supervised learning (SSL). Our model efficiently derives meaningful representations from raw ECG

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e-ISSN: 2468-4376
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signals by using a two-phase approach—self-supervised pre-training and supervised fine-tuning—so improving classification accuracy for several heart diseases. The assessment of publicly accessible datasets including PTB-XL and MIT-BIH shows the strength and efficiency of the model in practical settings. Together with reducing reliance on large annotated datasets, integrating SSL with deep learning provides a scalable solution for real-time ECG monitoring and early diagnosis. By allowing quick and accurate identification of heart illnesses and opening the path for more easily available and effective diagnosis tools, this method has great potential to improve cardiovascular healthcare. Future research could investigate how multimodal data and real-world deployment might be combined to improve clinical relevance even more.

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