Journal of Information Systems Engineering and Management
2025, 10(14s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

Risk Factor Analysis for Early Prediction of SCD in ECG Using BI-ANFIS

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ARTICLE INFO

Received: 18 Nov 2024

Revised: 05 Jan 2025

Accepted: 18 Jan 2025

ABSTRACT

One of the common outcomes of coronary artery disease (CAD) is Sudden Cardiac Death (SCD). Sudden cardiac arrest can lead to death without immediate treatment. The risk factors should be examined to analyse the risk level of SCD earlier. Nevertheless, it is challenging to analyse such parameters in Electrocardiogram (ECG) signals. Hence, the risk factors are analyzed in this article to predict the risk level of SCD utilizing a Bilinear Interpolation-based Adaptive Neuro-Fuzzy Inference System (BI-ANFIS) in ECG signal. Primarily, the ECG signal is taken as input and pre-processed for noise removal and frequency modulation correction. Afterward, by utilizing the Pan-Tompkins-based Hidden Markov Model (PT-HMM), the signal intervals are segmented. Thereafter, for analysing the first risk factor, the features from segmented waves are extracted, selected, and validated; also, CAD is predicted utilizing Soft plus error function-based Multi-Layer Perceptron (Serf-MLP). Concurrently, the smoke and QTc risk factors are evaluated. Now, the fourth risk factor is analyzed by the extraction of ST wave, J-wave selection, and type identification. Lastly, the BI-ANFIS is utilized to predict the SCD level of the ECG wave features grounded on the analyzed factors. Hence, the proposed technique's superiority over the conventional approaches is proved by the final outcomes.

Keywords: Sudden Cardiac Death (SCD), Electrocardiogram (ECG), coronary artery disease (CAD), Bilinear Interpolation-based Adaptive Neuro-Fuzzy Inference System (BI-ANFIS), Pan-Tompkins-based Hidden Markov Model (PT-HMM), SCD risk analysis.

1. INTRODUCTION

One of the severe outcomes of heart disease is SCD in which the survival rate of the patient is less than the other heart issues. However, the diagnosis of SCD risk level in a person at the early onset of symptoms remains very poor despite the advancement of medical technology (Pan et al., 2020). Therefore, the risk of SCD needs to be identified as early as possible. CAD is said to be the most general underlying condition that leads to SCD (Schröder et al., 2022). CAD occurs owing to atherosclerosis, which causes a narrowing of the artery lumen, thus leading to reduced blood flow being supplied to the distal myocardium (Alizadehsani et al., 2020). This results in arrhythmia. Hence, a significant role has been played by CAD detection in analyzing the risk factors of SCD. Nevertheless, SCD is not limited to only CAD syndrome, it may also occur owing to an extensive variety of various electrical substrates (Haleem et al., 2021). Therefore, to analyze the risk of SCD, the continuous monitoring of heart signals is necessary. For this purpose, researchers presently utilize numerous time-series systems, namely Photoplethysmograph, Phonocardiogram, and ECG to detect heart pathologies (Khan et al., 2022). Yet, an electrocardiograph, which is a graphic record of electrocardiography, is the most common test for heart conditions (Ahsanuzzaman et al., 2020).

The features in the heart's electrical signal are changed by cardiovascular issues. Identifying the SCD occurrence in the ECG signal earlier is possible if significant changes are found concerning a reference signal (healthy) (Velázquez-González et al., 2021). However, for the detection of SCD, there is a need for highly correlated variables, dynamic modelling, and nonlinear associations betwixt variables in conventional statistical methods (Jentzer et al., 2023). Hence, to enhance the SCD's risk prediction, the approach for efficient research is exemplified by the utilization of Machine Learning (ML) as well as Deep Learning (DL) mechanisms (Corianò & Tona, 2022). For the prediction of SCD, the DL mechanisms, namely Long Short Term Memory (LSTM) (Banerjee et al., 2020) and MLP-LSTM (Baral et al., 2021) are utilized. Yet, in ECG classification systems, the accuracy as well as speed of diagnosis of SCD risk are challenging; also, in the characterization of the true cause of SCD, these systems are challenged by the presence of noise, instability, and imbalance in heartbeats (Ha et al., 2022; Shoughi & Dowlatshahi, 2021). It is a great challenge to recognize those who benefit from an Implantable Cardioverter-Defibrillator (ICD) because SCD can be prevented in those who wear an ICD (Martinez-Alanis et al., 2020). Most studies failed to generate a visualization risk score even though some models derived from DL algorithms can accurately predict SCD (Wu et al., 2021). Therefore, this research proposes a risk-level analysis of the SCD using BI-ANFIS based on the high-risk factors.

1.1 Problem statements

Some of the shortcomings in the prevailing works for SCD's early diagnosis are given further,

- Even though SCD diagnosis models were developed, there was still no research for the prediction of the risk of occurrence of SCD grounded on the various risk factors.
- The risk factor analysis for SCD grounded on CAD in ECG poses a major challenge. Moreover, important risk factor, such as J-wave syndrome is neglected.
- The lack of proper feature selection and validation of the more extracted features increased the time and decreased the efficiency of the CAD prediction model.
- The segmentation of the intervals centered on the onset of the s-point value from the PQRST wave is a challenging process.

By considering these limitations, the proposed technique aims to develop a suitable SCD risk-level diagnosis model based on the risk factor analysis.

The remaining article is formatted as; the related works are displayed in Section 2. The proposed mechanism is exemplified in Section 3. The experiential outcomes are elucidated in Section 4. The paper is wrapped up in Section 5.

2. RELATED LITERATURE WORKS

(Parsi et al., 2021) examined an automated prediction of SCD grounded on the selected features of heart rate variability in an Implantable ICD. For the SCD prediction, the infinite latent feature selection and the minimal Redundancy-Maximal Relevance (mRMR) were utilized to select the optimal features. The results proved that the features selected with mRMR achieved superior sensitivity and accuracy levels for Support Vector Machine (SVM) and Random Forest (RF) models. Yet, the significant number of feature calculations became a challenge for ICD, because of less storage resources in it.

(Gupta et al., 2023) proffered an ML technique to detect cardiac arrest earlier in newborn babies. The cardiac arrest was identified by the logistic regression and SVM grounded on the combined neonates' physiological parameters. The efficiency of cardiac arrest detection was proved by the higher accuracy and precision rate of this scheme. However, the early diagnosis performance was able to deteriorate without considering the previous health data.

(Shahid & Singh, 2020) presented a CAD diagnosis framework grounded on a hybrid approach. The hybrid approach was developed with Particle Swarm Optimization (PSO) and emotional neural networks. This hybrid model's performance was enhanced with features extracted utilizing fisher, relief-F, along with mRMR-based techniques. The attained higher rates of performance on experimental evaluation showed the introduced scheme's superiority. When more data was used, optimal features were not selected by the PSO.

(Atal & Singh, 2020) propounded an ECG signal-based arrhythmia classification grounded on the optimization-enabled Deep Convolutional Neural Network (DCNN). The features extracted by the Gabor filter were given to the DCNN in which the parameters were optimally tuned with the rider optimization approach as well as the multi-objective bat approach for arrhythmia classification. This classification framework attained better performance on parameters like accuracy and sensitivity. However, owing to the intervention of noise, this model could not localize the fiducial points in the ECG waves.

(Abdalla et al., 2020) exemplified an arrhythmia classification framework in the ECG signal grounded on a DCNN. 4 layers of convolution interchanged with 4 layers of max-pooling as well as 3 fully connected layers were the eleven layers for the heart abnormality classification utilized by the DCNN. The developed DCNN's reliability was proved for the arrhythmia classification grounded on the accuracy and Receiver Operating Characteristics (ROC) levels. Nevertheless, without the noise removal in the input ECG signal, the DCNN was unable to predict inaccurate results.

(Sridhar et al., 2021) examined non-linear features for detecting myocardial infarction in ECG signals. Here, the Pan-Tompkins (PT) approach detected the R peaks in the ECG signal. Non-linear features were extracted from the detected R peaks and then ranked, and further given to the KNN, SVM, DT, and Probabilistic Neural Network (PNN) to differentiate normal and myocardial infarction classes. This non-linear feature-based SVM model achieved superior performance on experimental analysis. Still, the non-linear method was computationally complex.

(Murugappan et al., 2021) established a morphological features-based framework for predicting SCD utilizing ECG signals. The morphological features, namely the Hurst exponent, approximate entropy, largest Lyapunov exponent, and sample entropy were extracted from the R peak to the T-end in the ECG signal. The experimental analysis exposed a higher SCD prediction rate for the SVM trained with the extracted features. Yet, the characteristics of the extracted features were altered by the interference of circadian rhythms, which resulted in incorrect predictions.

(Asgharzadeh-Bonab et al., 2020) recommended an ECG beat classification scheme grounded on the time-frequency features. The features were extracted with the time-frequency spectral entropy; then, with the 2-directional 2-dimensional principal component analysis, the feature dimensionality was reduced. Lastly, CNN classified the features into normal and arrhythmia classes. The efficiency of the CNN-based heartbeat classification model was proved by the comparative assessment of the accuracy level with the conventional works. However, this framework neglected to obtain high time resolution in the ECG signal, which could deteriorate the experimental outcomes.

3. PROPOSED RISK FACTOR ANALYSIS FOR THE SCD RISK LEVEL PREDICTION

The early diagnosis of SCD risk aids a physician in making appropriate decisions. However, the analysis of risk factors influencing SCD from the ECG signal is a complex process. Therefore, this research proposes the BI-ANFIS-based risk level prediction based on risk factor analysis, which is given in Figure 1.

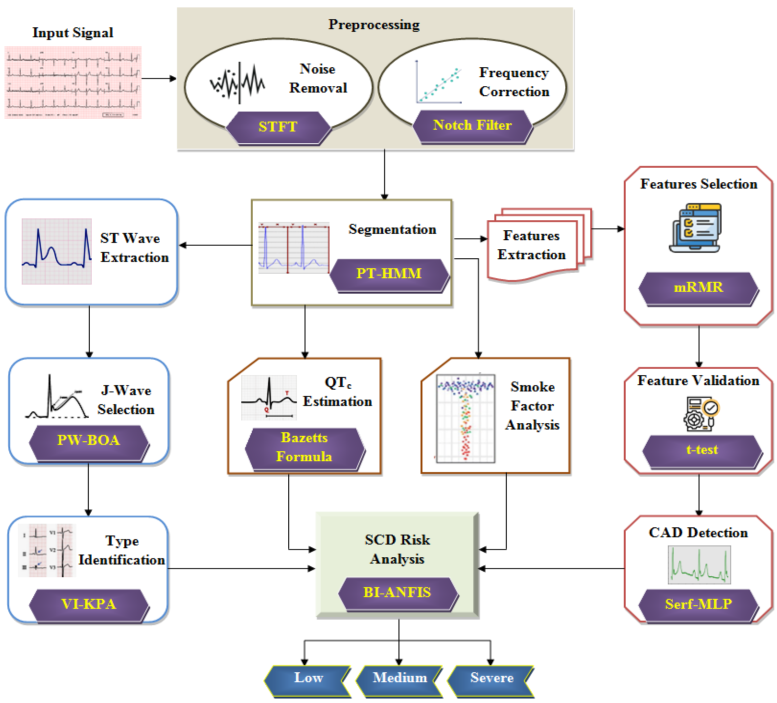

Figure 1: Proposed architecture for SCD risk level prediction

3.1 Input data

Here, the ECG signals of multiple patients who have normal heart conditions and heart failure are taken as input. The input signal is expressed as,

$$E_\alpha = \{E_1, E_2, \ldots, E_x\} \tag{1}$$

Where, E_α exemplifies the x number of ECG signals of patients.

3.2 Pre-processing

The input signals (E_α) are pre-processed since the accurate analysis of rhythms is hindered by the presence of artifacts in the ECG signal. Here, to obtain a clear ECG wave, the artifacts, namely noise and modulated frequency are processed.

3.2.1 Noise removal

The noise is generated in the ECG signal (E_α) by the griping force and other muscular actions. This noise is removed utilizing the Short-Time Fourier Transform (STFT) technique. To reconstruct a noise-removed signal, the STFT utilizes a window function $(\omega(f))$. For that, a symmetric half-cycle sine window is first estimated as,

$$\omega(f) = \sin\left(\frac{\pi}{F}(f + 0.5)\right), n = 0,..,F - 1 \tag{2}$$

Here, f specifies the F number of window lengths and F symbolizes the total window length. The signal E_α is taken in the z^{th} window block, $(z \in f)$ and is described as,

$$\zeta(z, \omega) = \Theta\{E_\alpha.\omega(f - z.F/2)\} \tag{3}$$

Wherein, Θ illustrates the discrete-time Fourier transform and $\zeta(.)$ exemplifies the STFT transformed signal. Afterward, to neglect the noise, the threshold of STFT is calculated as,

$$\zeta_2(z, \omega) = Q(\zeta(z, \omega)) \tag{4}$$

Here, $Q(.)$ symbolizes the thresholding function. The signal values below the threshold are set to 0. Thereafter, the Inverse STFT (β^{-1}) is taken to retrieve the noise-removed signal as,

$$X_\alpha(f) = \beta^{-1}(\zeta_2(z, \omega)) \tag{5}$$

Where, $X_\alpha(f)$ elucidates the noise-removed signal.

3.2.2 Frequency correction

The frequency correction is performed in the ECG signal $(X_\alpha(f))$ after denoising. The frequency modulation in the ECG signal occurs owing to breathing, thus creating interference in the heart waves. For this, the notch filter is employed for correcting the frequencies in the ECG signal. The notch filter, which neglects the frequencies of the signal at a very low level, is a band-pass filter.

3.3 Segmentation

Segmentation is done utilizing the PT-HMM to analyze each interval in the ECG wave λ_α. The HMM (Akhbari et al., 2016) is selected owing to the less segmentation error in ECG wave segmentation. However, the standard HMM lacks information about the states of the onset. Hence, to determine the wave information in ECG, the PT technique is utilized.

3.4 Analysis of Risk Factor 1

The first risk factor, which is the CAD, is detected by performing feature extraction, selection, validation, and prediction with the segmented signals to identify the risk level of SCD.

3.4.1 Feature extraction

The features, namely Hurst exponent, R-R intervals' root mean square, the number of adjacent R-R intervals, largest Lyapunov exponent, entropies, standard deviation, and mean are extracted from the segmented signal wave S.

3.4.2 Feature selection

By using the mRMR technique, the less correlated features and relevance features that are more relevant to the CAD class are selected from the extracted features.

3.4.3 Feature validation

To ensure that the selected features can really enhance the CAD prediction model's performance, the selected features are validated using the t-test. The large t-test score specifies that the features correspond to different groups.

3.4.4 CAD detection

With the validated features, the CAD in the patient's ECG is detected using the Serf-MLP algorithm. Here, the MLP (Mirjalili et al., 2020) is selected as it could learn non-linear relationships between the features of different classes effectively. The ReLu activation in the hidden layers of MLP induced dying ReLu, which leads to the neurons being inactive in the MLP network. Hence, the Serf technique is utilized in the MLP to activate the neurons effectively.

Input layer: The Serf-MLP's input layer receives the validated features of the segmented ECG waves. These features are prepared for processing in the other layers. The validated features given as the input are represented as,

$$\upsilon_g = \{\upsilon_1, \upsilon_2, .., \upsilon_y\} \tag{6}$$

Where, υ_g implies the y number of validated features.

Hidden layers: From the input layer, the prepared υ_g is given to hidden layers. Here, to differentiate the final output, the non-linearity between the features is learned. Each hidden layer in Serf-MLP generates individual output (λ_κ) by using the hidden neuron as,

$$\lambda_\kappa = \nabla\left(\sum_{\kappa=1}^{p} \varpi_\kappa^\vartheta . \upsilon_g + \Re^\vartheta\right) \tag{7}$$

Where, $\Re^\vartheta$ illustrates the bias value of the hidden layer (ϑ), the total number of hidden neurons is displayed as p, ϖ_κ^ϑ signifies the weight value of κ^{th} hidden neuron of the ϑ^{th} layer, and $\nabla(.)$ defines the serf activation function, which can be defined as,

$$\nabla(\lambda_\kappa) = \lambda_\kappa \Re(\ln(1 + \exp(\lambda_\kappa))) \tag{8}$$

Where, $\Re(.)$ illustrates the error function, and $\ln, \exp$ signify the natural logarithm and exponential functions, correspondingly.

Output layer: After that, to predict the output class (O_{out}), the processed outputs (λ_κ) from the hidden neurons are summed up and given to the output layer. The output of the Serf-MLP is expressed as,

$$O_{out} = \nabla\left(\sum_{\kappa=1}^{p} \lambda_{\kappa}.\varpi_{out} + \Re_{out}\right) \tag{9}$$

Here, $\varpi_{out}, \Re_{out}$ illustrate the weight value and bias value of the output neuron. For the output O_{out}, the loss function is calculated to predict whether the output reached the target t_{out} as,

$$loss = \frac{1}{y}\sum_{g=1}^{y}(O_{out} - t_{out}) \tag{10}$$

Here, y represents the total number of inputs. The output class will be considered if the estimated error value $(loss)$ is less than or equal to the threshold (Tr); or else, the training continues by changing the weight values. By doing this in ECG, the presence of CAD can be detected, and the class of CAD is symbolized as (C_1), and the normal heart class is notated as (C_0).

3.5 Analysis of Risk factor 2 and 3

Concurrently, the other risk factors of SCD, namely QTc interval and smoke factor analysis are analyzed in the segmented ECG signal.

QTc interval analysis: A chief role is played by the prolonged QTc interval in the occurrence of SCD. The QTc interval is determined utilizing the Bazzets' formula (BF)

Smoke factor analysis: Thereafter, to predict the SCD risk level, smoking, which is also one of the risk factors of SCD, is evaluated.

3.6 Analysis of Risk Factor 4

The J-wave syndrome plays a significant role in the prediction of the risk levels of SCD, but it was neglected as noise while predicting heart diseases. The type of J-wave mirrors the risk level of SCD. Therefore, in this research, the J-wave syndrome is analyzed as the risk factor for SCD. The processes, such as ST wave extraction, J-wave selection, and level prediction, are performed to detect the level of J-wave.

3.6.1 ST wave extraction

The ST wave interval (I_{sst}), which contains multiple signal points, is extracted from the segmented signals.

3.6.2 J-Wave selection

Thereafter, to select the curve points corresponding to J-wave, the curve points of I_{sst} are given to the Parzen Window-based Billiards Optimization Algorithm (PW-BOA). Here, the BOA is selected owing to the advantage of balancing the features in the exploration and exploitation phase. However, a slow convergence rate is introduced by the random initialization of the balls. Hence, using the Parzen window technique, the position of the ball is determined.

3.7 SCD Risk Prediction

After analzing the four types of risk factors, the risk of SCD is predicted based on these factors. Here, the BI-ANFIS is proposed for the risk level prediction. The ANFIS (Akhbari et al., 2016) is selected since it possesses less memorization error for the prediction of the risk level. However, the ANFIS had the limitation of creating errors for the updation of the parameters of the network. Hence, the Bilinear Interpolation (BI) technique is utilized in the ANFIS to select the most adaptable parameters.

4. RESULTS AND DISCUSSION

This phase assesses the proposed technique's performance, and the experiments were conducted in the working platform of PYTHON.

4.1. Dataset description

For cardiac arrhythmia analysis and detection, the Massachusetts Institute of Technology-Beth Israel Hospital (MIT-BIH) Arrhythmia Database is a widely utilized dataset. 48 half-hour ECG recordings acquired from 47 subjects are enclosed in the database. Each subject is associated with different ECG records that capture the heart's electrical activity over time. The recordings are digitized at a sampling rate of 360 samples per second, thus providing the ECG signal's high-resolution representation.

4.2. Performance Analysis

Here, the performance as well as comparative analysis take place to validate the efficiency of the proposed model.

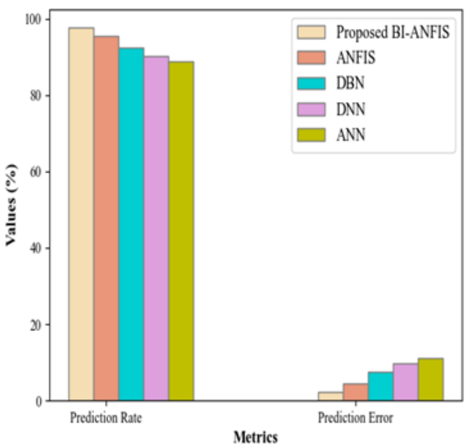

Figure 2: Prediction rate and prediction error comparison

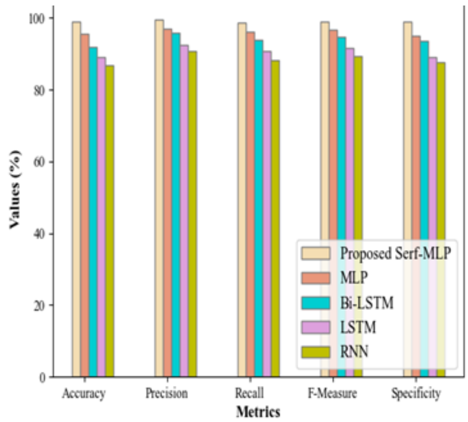

Figure 3: Comparative analysis of the proposed Serf-MLP

The prediction rate and prediction error of the proposed BI-ANFIS and the existing ANFIS, Deep Neural Network (DNN), Deep Belief Network (DBN), and Artificial Neural Network (ANN) are presented in Figure 2. The proposed BI-ANFIS model demonstrates the highest prediction rate (97.63%) with a relatively low prediction error (2.296%). However, the existing works remain with an average prediction rate of 91.72% and a prediction error of 8.23%. As per the outcomes, the proposed BI-ANFIS performs better than other conventional systems. This is because the proposed BI-ANFIS adjusts its parameters dynamically during the learning process, and learns complex relationships, which results in improved prediction accuracy.

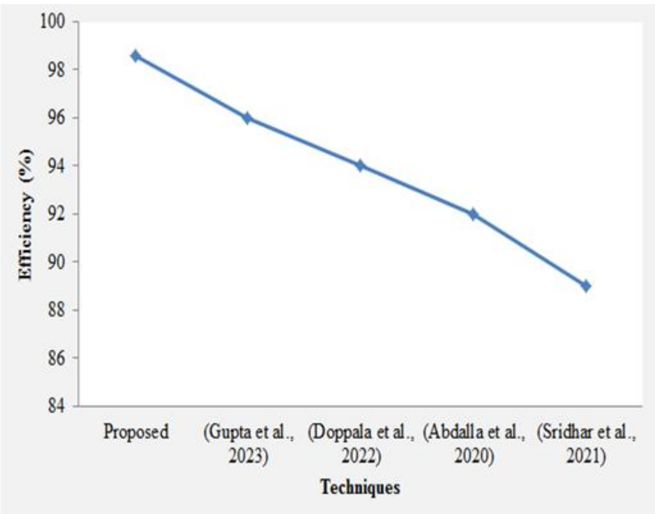

Figure 4: Efficiency comparison with related works

The accuracy, recall, f-measure, precision, and specificity of the proposed Serf-MLP and the conventional MLP, Bidirectional LSTM (Bi-LSTM), LSTM, and Recurrent Neural Network (RNN) are compared in Figure 3. The problem of dying ReLU is addressed by the Softplus error function in Serf-MLP and ensures that all neurons remain active during training. By combining the benefits of the Serf and MLP architecture, the proposed Serf-MLP achieves better performance accuracy (98.97%), precision (99.46%), recall (98.73%), F-Measure (99.06%), and specificity (98.83%) compared to traditional methods. Hence, the proposed Serf-MLP is more efficient in CAD detection.

The efficiency of the proposed and the existing methods is compared in Figure 4. The proposed model incorporates a well-designed feature selection and validation process. The model can reduce the data's dimensionality by selecting relevant and informative features from the ECG signal, thus resulting in faster computation and enhanced efficiency. Moreover, the validation step ensures that the chosen features are robust and have a meaningful impact on the SCD prediction, thus avoiding unnecessary computational overhead. These factors ensure better efficiency (98.57%) of the model.

5. CONCLUSION

This article proposed a BI-ANFIS-based risk factor analysis for the early prediction of SCD using ECG signal analysis. BI-ANFIS, Serf-MLP techniques are combined by the proposed model, thus resulting in high accuracy in the recognition of risk levels for SCD. Also, it efficiently handles complex non-linear relationships, reduces memorization errors, and accurately identifies risk levels for SCD. The proposed mechanism's performance is validated by the experimental analysis. The proposed system, which provides auspicious outcomes, could handle several uncertainties. For the analysis, the MIT-BIH Arrhythmia Database is utilized in which the proposed method withstands the highest prediction rate of 97.63% with a low prediction error of 2.29%. Therefore, the proposed mechanism performs superior to the conventional approaches and remains to be more reliable as well as robust. Yet, the ECG signals are only concentrated by the proposed system. The future work would integrate multiple data sources, namely ECG, imaging, and patient demographics. This can further enhance the model's accuracy and robustness in CAD risk prediction.

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