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RESEARCH ARTICLE

CAD-SULOR: CARDIOVASCULAR DISEASE CLASSIFICATION USING MACHINE LEARNING BASED SUPPORT VECTOR MACHINE AND LOGISTIC REGRESSION

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Abstract – cardiovascular diseases (CVD) are found to be rampant in the populace leading to fatal death. Worldwide, the majority of people are suffering from CVD. However, the performance of current deep learning models is heavily reliant on the availability of large, well-annotated training datasets, which are frequently difficult to obtain in the medical domain due to privacy concerns and labeling costs. Inadequate or imbalanced data might cause biased predictions, lowering the model's reliability in detecting fewer common arrhythmias and possibly leading to diagnostic errors in essential cases. In this study a novel Machine learning-based CAD-SULOR model is proposed for CVD using support vector machine (SVM) and logistic regression (LR). The input signal is pre-processed using Least mean square (LMS) algorithm to reduce the noise and enhance the signal. Discrete Wavelet Transformation (DWT) is used to extract the features from the ECG signal. The SVM, and LR are utilized to improve the accuracy and classify the CVD, such as normal and abnormal. The performance of the CAD-SULOR approaches was assessed using the metrics such as F1 score, specificity, recall, accuracy, and precision. The CAD-SULOR approach achieves a high accuracy of 99.26% for cloth retrieval. The CAD-SULOR the accuracy 8.36%, 2.84% and 0.39% better than DDR-Net [13], MobileNet [14], and LSTM [16] respectively.

Keywords *– Cardiovascular Diseases, Least mean square, Discrete Wavelet Transformation, support vector machine, logistic regression.*

1. INTRODUCTION

Cardiovascular Disease (CVD) is an overall term referring to the conditions that affect the heart and blood vessels of a human body [1]. In recent years, millions of individuals around the world have perished as a result of CVD. Heart attacks, ischemic strokes, hemorrhagic strokes, heart failure, different arrhythmias, and valve difficulties are among the most common CVDs [2].

The World Health Organization (WHO) defines health as a fundamental human right. The global population is currently at risk from a variety of widespread illnesses that could be fatal. According to the WHO, heart disease causes 17.7 million deaths per year, or 31% of all fatalities worldwide [3]. Electrocardiogram (ECG) [4, 5] is a convenient and effective method for monitoring heart activity, used to evaluate heart health and diagnose cardiovascular diseases [6].

Machine learning (ML), which enables automated, efficient, and highly accurate analysis of complex datasets, has transformed medical imaging [7]. ML and deep learning (DL) classifiers have recently been developed to identify and categorize CVD from ECG data [8, 9]. Several ML techniques, including Random Forest (RF), SVM, LR, and Backpropagation Neural Network (BPNN), have been effectively employed as decision-making tools for CVD prediction based on the data [10, 11]. In the field of CVD classification, deep neural networks (DNN) are appealing due to their automated feature recognition and extraction strategy, which produces dependable and visible outcomes [12].

However, the complexity of multi-criteria Bayesian optimization and the hybrid filtering process increases implementation time and computing cost, potentially making it unsuitable for real-time applications or deployment on medical devices with restricted resources. Additionally, fine-tuning certain filter settings and deep learning model components requires a high level of domain expertise, limiting the system's potential for widespread clinical use in the absence of expert assistance. To overcome this problem, the CAD-SULOR approach for CVD. The important contributions of the CAD-SULOR approaches are as follows:

- The input images are denoised using the Least mean square to enhance the ECG signal, and DWT is used to extract the features of the signal.
- The SVM and LR are used to improve the accuracy and classify the CVD, such as normal and abnormal.
- The CAD-SULOR model efficiency was assessed using metrics like F1 score, specificity, recall, accuracy, and precision.

The structure of this paper and other parts of this work is as follows: Section 2 presents the literature review. The CVD classification is explained in Section 3, while the findings and discussion of the CAD-SULOR approaches are explained in Section 4. The conclusion and recommendations for further research are included in Section 5.

2. LITERATURE SURVEY

In this paper, researchers have proposed a number of advanced machine learning (ML) and DL designs for CVD. SVM, CNN, and AlexNet have been used with various techniques and designs for CVD in the research studies that have been proposed. Some of the research are examined in the following section.

In 2025, Zhu et al. [13] proposed a dual-scale deep residual networks (DDR-Net) are used to extract characteristics from raw PCG and ECG signals. SVM is used for final classification once critical attributes have been determined using SVM-RFECV. The experimental results show that our method outperforms before multi-modal studies and methods that simply use PCG or ECG, with an accuracy of 91.6% and an AUC value of 0.962.

In 2025 Alsayat et al, [14] provided a DL algorithm to classify ECG images and identify various heart conditions. This investigation carefully assesses the performance of pre-trained neural networks updated using transfer learning in order to demonstrate the revolutionary influence of these technologies in improving cardiology diagnoses. The model showed remarkable prediction abilities, with a balanced accuracy of 96.40%.

In 2025 Anand et al. [15] proposed a WT-based convolution algorithm are used to extract features from CXR images and ECG signals, both in one and two dimensions. Six ML and four DL models were developed for HD detection, with these properties serving as inputs to AI-based detection models. Performance metrics such as WT-based circular convolution and classification accuracy (0.94) offer a practical and effective method for diagnosing heart disease in real time.

In 2025 Mandala et al. [16] developed a DL based OCADN model capable of automatically detecting four types of arrhythmias from ECG signals using the MIT-BIH database. The consistent performance of OCADN on both datasets indicates its robustness and potential for clinical implementation. OCADN with hyperparameter tuning exhibits accuracy of 98.87% respectively, on the training data.

In 2025 Qureshi et al. [17] presented a DL-based method for MIT-BIH arrhythmia-based automated ECG heartbeat classification. The system classified ECG heartbeats using CNN and AlexNet models. The proposed Alex Net model achieves a 99.68% overall classification accuracy.

In 2025 Bentaleb et al. [18] developed a new advanced model for ECG signal denoising and categorization, combine a hybrid filter with Bayesian optimization (BO) techniques. Cross-correlation and MSE are two significant indicators utilized in the multi-criteria BO method for fine-tuning filter parameters and improving signal quality. After filtering, the data illustrate a significant improvement in classification accuracy of 96.63%.

In 2025 Chandrasekhar et al. [19] proposed PJM-DJRNN is an innovative HD classification accuracy prediction approach based on the Polynomial Jacobian Matrix. The proposed method decomposes the signals using HEEMD and then classifies them into normal and abnormal categories using RFFC. The proposed model's categorization efficacy was proven through experimental studies, obtaining an accuracy of 97.33%.

In the literature review, these current approaches have several limitations like difficulty in classifying CVD because of low-quality signals, especially in real-world clinical settings where data variability is high. To overcome this problem, the CAD-SULOR approach in CVD.

3. PROPOSED METHODOLOGY

In this paper, a novel CAD-SULOR approach classify the CVD in ECG signal. The ECG signal are denoised using the least mean square (LMS) algorithm to Remove muscle artifacts. Discrete Wavelet Transformation (DWT) is employed to extract features and edge identification for real-time classification in CVD. The hybrid classification is used in SVM and LR, improving accuracy and classification, such as distinguishing between normal and abnormal. The overall process of the CAD-SULOR approach is illustrated in Figure 1.

3.1. Data description

In this study, the ECG Heartbeat Categorization Dataset for CVD categorization was obtained from Kaggle. The MIT-BIH Arrhythmia Dataset and the PTB Diagnostic ECG Database are two important heartbeat classification datasets from which two sets of heartbeat signals were extracted. The 109446 samples in both collections are sufficient for training a DNN at 125 Hz. Using DNN architectures, this dataset was used to examine heartbeat categorization and observe some transfer learning skills. The signals correspond to the heartbeat patterns on an electrocardiogram (ECG) in both normal and arrhythmia- and myocardial infarction-affected conditions.

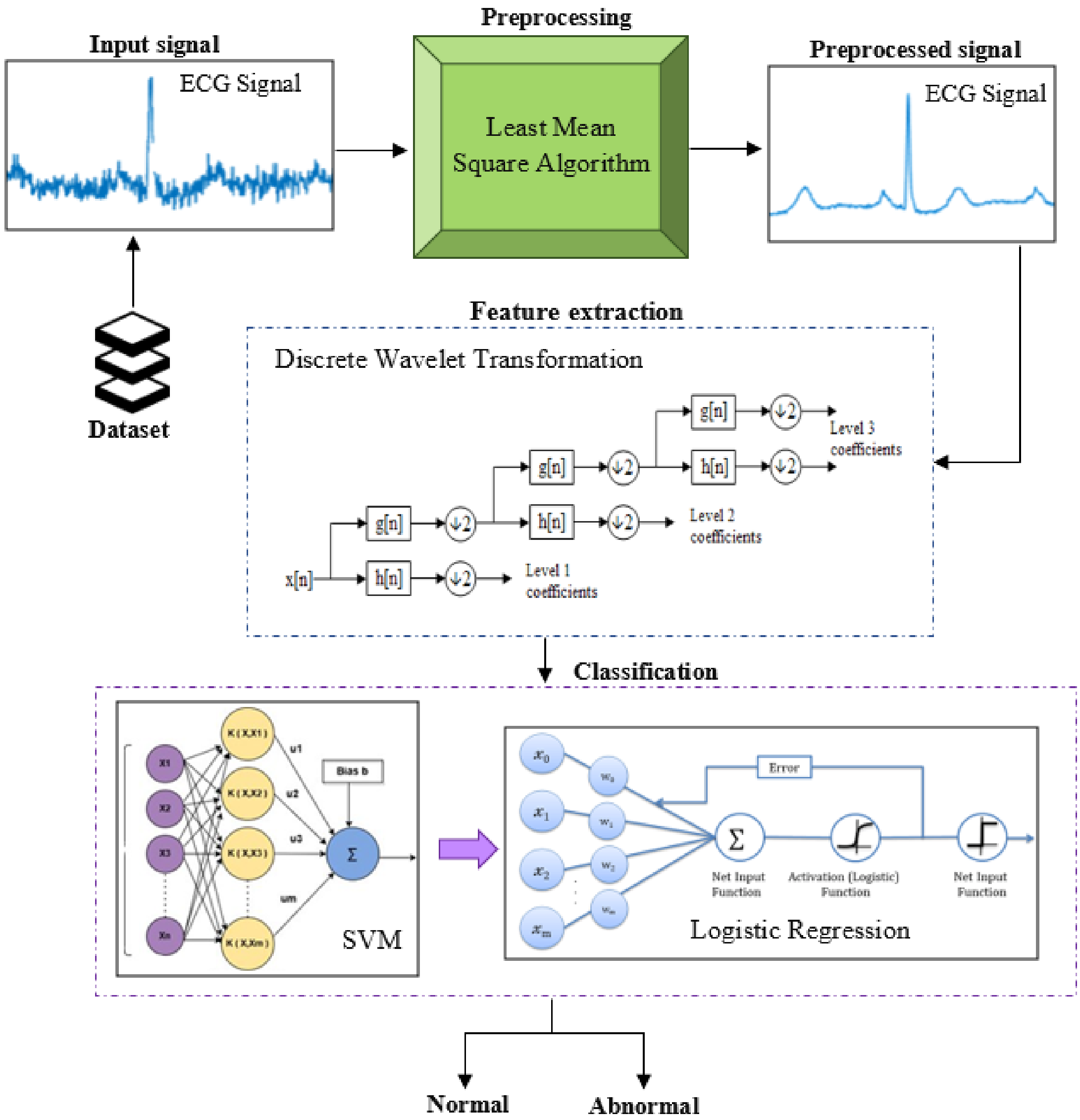


Figure 1. Workflow of the CAD-SULOR Model

3.2. Preprocessing

Least Mean Squares (LMS) are commonly employed in the Adaptive Filters (AF) technique to reduce noise and improve ECG signal quality. The weight update equation below is used to change the FIR filter coefficients in each iteration of the standard LMS algorithm.

$$w(n+1) = w(n) + \mu x(n)e(n) \quad (1)$$

where $n, w(n)$, and $w(n+1)$ represent the time step, old weight, and updated weight, respectively. The filter input is denoted by $x(n)$, the error signal $e(n)$ defines the weight update of filter coefficients, and the step size μ regulates the filter's stability and convergence. Equation (2) is then used to determine the AF output, $y(n)$, using the altered weight and input.

$$y(n) = w^t(n)x(n) \quad (2)$$

$$e(n) = d(n) - w^t(n)x(n) \quad (3)$$

The LMS filter modeling assumes that the input ECG signal $x(n)$ is contaminated by additive noise $v(n)$.

3.3. Feature extraction

Discrete Wavelet Transformation (DWT) is a signal processing method that uses mathematical models to reveal an investigated signal's properties. This method assumes that the signal under analysis is made up of a collection of similarly tiny functions, called the mother wavelet, which is made up of scaling and shifting.

$$\varphi_{a,b}(t) = \frac{1}{\sqrt{a}}\varphi\left(\frac{t-b}{a}\right) \quad (4)$$

where t is the time, a and b are the scaling and shifting parameters, and $\varphi(t)$ is the mother wavelet function. The DWT is easily determined using the mother wavelet's scale and shifting position.

$$DWT(m,n) = \frac{1}{\sqrt{a_0^m}}\sum_k f(k)\varphi\left[\frac{n-kb_0a_0^m}{a_0^m}\right] \quad (5)$$

where n denotes the number of points and m and k are the scaling and shifting coefficients. To produce the high-frequency (HF) and low-frequency (LF) coefficients, the Mallat algorithm uses low-pass and high-pass filters to remove the HF and LF components of a signal under research on respectively. In total layers of DWT using the Daubechies 6 (db6) mother wavelet were applied to the CVD of ECG. Normal beats recorded from four cases were utilized to calculate their coefficients. For feature extraction, detailed coefficients were extracted from each ECG pulse. Because the resulting sub-band coefficients were related to the type of wavelet source, DWT with orders 1-5, orders 1-3, and other wavelet functions with varying degrees of decomposition were examined for improved CVD prediction classification accuracy.

3.4. Classification

Support Vector Machines (SVMs) are supervised classification-based machine learning techniques that may be quickly applied to a variety of classification and regression tasks. This is also widely used to overcome classification and regression issues. An n-dimensional neighborhood is utilized to investigate the technique as a transition phase, where n represents the number of features. It is used to address complex problems that do not have straightforward solutions. Non-linear solutions to any problem are easily found efficiently with SVM by using a kernel trick function. Plotting the statistics in a high-dimensional region allows SVM to divide the task incrementally. A fully trained classification system is able to categorize any test sequence while also predicting training scenarios.

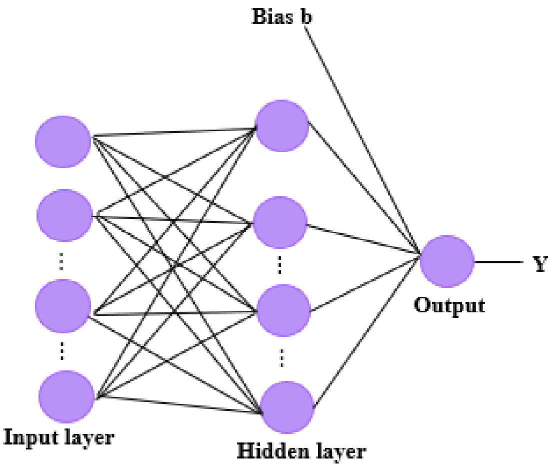


Figure 2. Architecture of Support vector machine

$$F(Xi) = [WXi + b] \tag{6}$$

$$F(Xi) = [W1 * X1 + W2 * X2 + b] \tag{7}$$

Logistic regression (LR), a common machine-learning approach for supervised binary classification, predicts the probability of response variables by using a collection of explanatory independent factors. It is a statistical strategy for forecasting data based on previous results from the provided data set. The architecture of LR is illustrate the figure 3. The LR approach uses one or more pre-existing predictor factors to forecast a wide variety of data properties.

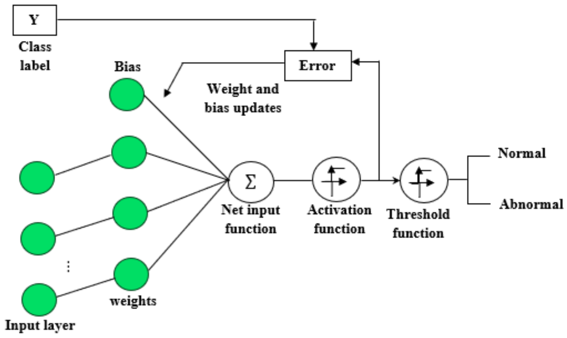


Figure 3. Architecture of Logistic Regression

$$Y = \frac{[e^{(\beta0+\beta1*x+\beta2)}]}{[(1+e^{(\beta0+\beta1*x+\beta2)})]} \tag{8}$$

where $\beta0, and\ \beta1$ indicate the bias term, which is the single data value coefficient (x), whereas $\beta2$ represents the double value. Each component of the data input should teach the training examples the β coefficient, which is the genuine, stable statistic.

4. RESULT AND DISCUSSION

In this section, the experimental set up of the CAD-SULOR was implemented using MATLAB 2020b. The CAD-SULOR to evaluate the approach of the collected ECG signal, a number of measures were employed, including F1 score, recall, accuracy, specificity, and precision.

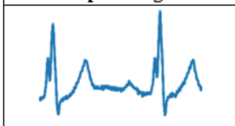
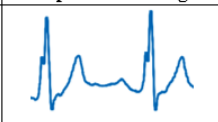
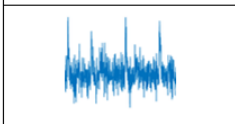
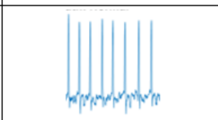
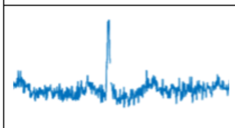
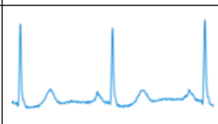
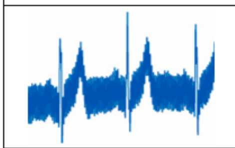
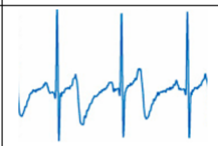
Input image	Preprocessed Image	Classification
		Normal
		Abnormal
		Normal
		Abnormal

Figure 4. Experimental result of the CAD-SULOR

The input signals are obtained from the ECG Heartbeat Categorization dataset, as shown in column 1. In column 2, the LMS is used to preprocessing step to remove the unwanted noise. Finally, the hybrid model is used to classify the CVD such as normal and abnormal. Figure 4 demonstrates the experimental results for the CAD-SULOR method.

4.1 Performance Analysis

This section assessed the CAD-SULOR approach using a number of measurements from the collected dataset, include recall, specificity, F1 score, accuracy, and precision.

$$accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (9)$$

$$Specificity = \frac{TN}{TN+FP} \quad (10)$$

$$Precision = \frac{TP}{TP+FP} \quad (11)$$

$$recall = \frac{TP}{TP+FN} \quad (12)$$

$$f_1 = 2(\frac{precision*recall}{precision+recall}) \quad (13)$$

where T_{pos} and T_{neg} indicates the true positive and negative of the provided images, F_{pos} and F_{neg} display the sample images false positives and negatives.

Table 1. Performance analysis of the CAD-SULOR model

Classes	Accuracy	Specificity	Precision	Recall	F1 score
Normal	99.55%	97.98%	94.57 %	96.97 %	98.58 %
Abnormal	98.96%	94.36%	95.95 %	98.28 %	97.90 %

The recall, F1 score, specificity, accuracy, and precision of the proposed method were assessed in Table 1. The proposed CAD-SULOR method's accuracy is 99.55% for normal and 98.96% for abnormal.

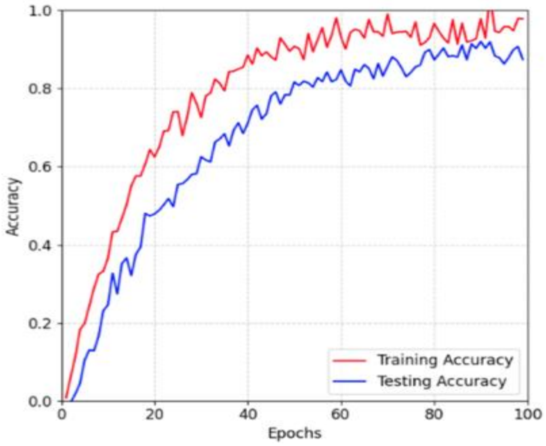


Figure 5. Accuracy of the proposed CAD-SULOR model

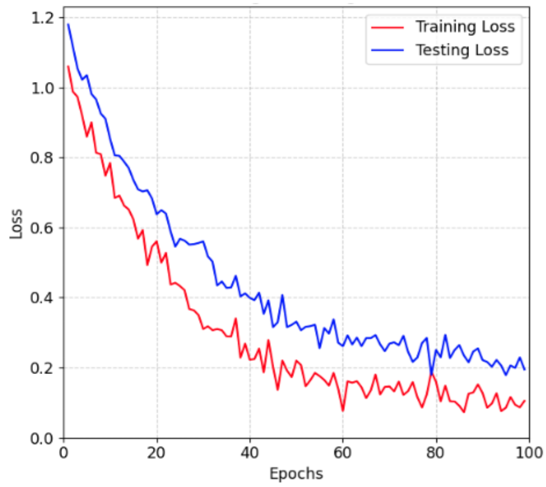


Figure 6. Loss of the proposed CAD-SULOR model

Figure 5 illustrate the accuracy of the training and testing, with accuracy on the y-axis and Epochs on the x-axis. The proposed framework shows an accuracy level of 99.26% for times when considering the correctness of its evaluation and training curves. The loss graph plotted against epochs in Figure 6 shows that the loss falls with increasing epochs. The CAD-SULOR approach achieves high precision with a low loss of 0.74%.

4.2 Comparative Analysis

The CAD-SULOR methods accuracy and efficiency were demonstrated by comparing it to other existing methods. The SVM and LR is used to enhance the accuracy of SVD classification. The effectiveness of the CAD-SULOR strategy was evaluated using metrics of recall, F1 score, accuracy, and specificity. The accuracy rate illustrates that the CAD-SULOR approach outperforms the current techniques. A comparison is performed between the CAD-SULOR approach and current approaches such as DDR-Net [13], MobileNet [14], and LSTM [16].

Table 2. Comparison of the existing dataset and CAD-SULOR model

Techniques	Accuracy	Specificity	Precision	Recall	F1 score
DDR-Net [13]	91.6%	90.56%	88.24 %	85.25 %	90.11 %
MobileNet [14]	96.51 %	94.23%	90.36 %	92.33 %	91.23 %
LSTM [16]	98.87 %	95.66%	97.34 %	92.45 %	95.52 %
Proposed	99.26 %	96.17%	95.26 %	97.62 %	98.24 %

Table 2 presents the various techniques of the existing model and compare the proposed model. The CAD-SULOR the accuracy 8.36%, 2.84% and 0.39% better than DDR-Net [13], MobileNet [14], and LSTM [16] respectively. The CAD-SULOR approach outperforms the current methods with an accuracy of 99.26%.

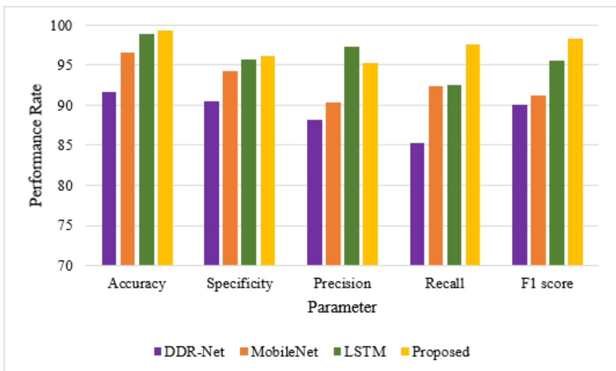


Figure 7. Comparison of the existing and proposed method

Figure 7 display that the comparative analysis of the existing method and CAD-SULOR approach. It achieves an 99.26% accuracy, 96.17% specificity, 95.26% precision, 97.62% recall, and 98.24% F1 score respectively. The CAD-SULOR improves the accuracy range of 8.36%, 2.84% and 0.39% better than DDR-Net [13], MobileNet [14], and LSTM [16] respectively. The CAD-SULOR methodology outperforms the current approaches with an accuracy of 99.26%.

Table 3. Accuracy comparison of the existing model and CAD-SULOR model

Authors	Method	Accuracy
Qureshi et al., [17]	AlexNet	98.99%
Bentaleb et al., [18]	EEMD	96.63%
Chandrasekhar et al., [19]	PJM-DJRNN	97.33
Proposed	CAD-SULOR	99.26%

Table 3 illustrates an accuracy comparison of current approaches and the CAD-SULOR approach. The CAD-SULOR maintains high accuracy levels of 99.26%. The CAD-SULOR approach enhances the total accuracy by 6.4%, and 1.3% better than AlexNet [12], EEMD [18], and PJM-DJRNN [19] respectively. According to the above comparison, the CAD-SULOR approach is more accurate than the existing models.

5. CONCLUSION

In this research, a novel CAD-SULOR approach was proposed for the cardiovascular disease classification using an SVM and LR. The input images were pre-processed using the LMS algorithm to reduce the noise and enhanced signal. The DWT is used to extract the features of an ECG signal. The SVM and LR is used to improve the accuracy and classification such as normal and abnormal. The performance of the CAD-SULOR approaches was assessed using the metrics such as F1 score, specificity, recall, accuracy, and precision. The CAD-SULOR approach accomplishes a higher accuracy of 99.26% respectively. The CAD-SULOR approach enhances the total accuracy by 6.4%, and 1.3% better than AlexNet, EEMD, and PJM-DJRNN respectively. The CAD-SULOR improves the accuracy range of 8.36%, 2.84% and 0.39% better than DDR-Net, MobileNet, and LSTM respectively. Future work will focus on enhancing the CAD-SULOR model for CVD by implement an advanced optimization technique to detect the CVD.

CONFLICTS OF INTEREST

The authors declare that there is no conflict of interest.

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