Online-Journals.org

iJOE International Journal of Online and Biomedical Engineering

iJOE | eISSN: 2626-8493 | Vol. 22 No. 9 (2026) | OPEN ACCESS

https://doi.org/10.3991/ijoe.v22i09.61197

PAPER

Hybrid Deep Learning Structure for Classifying ECG Signals Using CNN, MVO-Based Feature Selection, and SVM

Shelan K. Ahmed[1,2] (✉), Serwan A. Mohammed[2], Ahmed Kh. Mohammed[2]

[1]Duhok Polytechnic University, Duhok, Iraq

[2]University of Duhok, Duhok, Iraq

shelan.kamal@dpu.edu.krd

ABSTRACT

An accurate and effective heart disease diagnosis through the electrocardiogram (ECG) analysis remains the crucial issue in clinical practice due to complexity and nonlinearity of ECG patterns, morphological variability, and noise interference. This study proposes a hybrid framework that combines a convolutional neural network (CNN) with a support vector machine (SVM) for ECG signal classification. In the proposed hybrid model, feature extraction was done with CNN. Then, a multi-verse optimizer was used for feature selection. The classifier of the hybrid model is an SVM. The proposed hybrid model is trained and evaluated on the standard publicly available QT database (QTDB). Spectrogram and scalogram images generated from individual ECG beats were used as input to the proposed model. The 512 features obtained with spectrogram and scalogram images decreased to 259 features. The same dataset was used to determine the classification accuracy, which was 99.29% for scalogram-based images and 92.12% for spectrogram-based images. This notable enhancement shows that, in comparison to spectrograms, scalogram representations offer better distinguish features for classification of ECG signals. Moreover, a proposed method outperformed existing techniques. A paired t-test confirmed that proposed method significantly improved accuracy compared with CNN+SVM ($p < 0.0001$).

KEYWORDS

convolutional neural network (CNN), electrocardiogram (ECG), feature selection, metaheuristic optimization, multi-verse optimizer (MVO), scalogram, spectrogram

1 INTRODUCTION

Heart failure is a major global health problem affecting millions of people and placing a significant burden on healthcare systems [1]. Early and accurate diagnosis is essential for effective treatment and improved clinical outcomes. Electrocardiography (ECG) is one of the most widely used tools for detecting

Ahmed, S.K., Mohammed, S.A., Mohammed, A.K. (2026). Hybrid Deep Learning Structure for Classifying ECG Signals Using CNN, MVO-Based Feature Selection, and SVM. *International Journal of Online and Biomedical Engineering (iJOE)*, 22(9), pp. 106–125. https://doi.org/10.3991/ijoe.v22i09.61197

Article submitted 2026-02-19. Revision uploaded 2026-06-02. Final acceptance 2026-06-03.

cardiovascular diseases because it provides a non-invasive assessment of the heart's electrical activity [2]. However, traditional ECG interpretation relies heavily on expert analysis and may be affected by subjectivity and human error, leading to delayed or inaccurate diagnoses [3]. Recent advances in artificial intelligence (AI) and deep learning (DL) have transformed medical diagnosis by enabling automated feature extraction and classification from ECG signals. Deep learning models, particularly convolutional neural networks (CNNs), have demonstrated remarkable performance in analyzing complex ECG data and improving diagnostic accuracy [4], [5], [6]. These approaches offer an efficient and reliable alternative to conventional methods for the detection and classification of cardiovascular diseases. CNN are widely used for image processing and classification because they can automatically learn hierarchical features through convolutional, pooling, and fully connected layers. Unlike traditional machine learning methods, CNN integrate feature extraction and classification within a single framework, eliminating the need for manual feature engineering [7]. However, not all extracted features are equally informative, and redundant features may increase computational complexity while reducing classification performance [8], [9]. Therefore, feature selection methods, particularly metaheuristic optimization algorithms, are often applied to identify the most discriminative features. Recent studies have shown that combining CNN-based feature extraction with feature selection and SVM classifiers can improve both classification accuracy and computational efficiency [10], [11].

The key contributions and advantages of proposed model are summarized as follows:

I. This study proposes a hybrid model combining CNN, multi-verse optimizer (MVO), and SVM for improved classification of ECG signals.
II. Spectrogram and scalogram images from the QTDB database are used as inputs for the CNN. This allows for the extraction of time-frequency information. MVO is then used to reduce feature size by selecting the most relevant features.
III. The carefully selected collection of features is sorted using SVM. The research looks at how the optimization stage impacts both feature size and categorization accuracy.
IV. This study makes a significant contribution to the field by showing meta-heuristic feature selection is effective for ECG spectrogram/scalogram features. It gives an applicable hybrid model that can help guide future ECG signal work.

The remainder of this paper is structured as follows: Section 2 provides information about the studies carried out in literature. Section 3 provides information about the methods used in our research, database, and the MVO algorithm used in feature selection. Section 4 discusses the experimental results while Section 5 presents conclusions along with directions for future work.

2 RELATED WORKS

Electrocardiogram signal analysis has attracted significant research interest, and deep learning-based approaches have increasingly replaced traditional methods due to their superior performance in handling large and complex datasets. Shu Lih et al. [12] combined CNN and LSTM networks for arrhythmia detection using variable-length heartbeats, achieving improved classification performance, although the model was affected by dataset imbalance. Londhe and Atulkar [13] proposed a hybrid channel-mix CNN and bidirectional LSTM model for ECG wave segmentation, while Nurmaini et al. [14] developed a bidirectional LSTM-based framework for automatic ECG waveform delineation. Despite their effectiveness, both approaches face challenges related to generalization across diverse ECG datasets. Recent studies have focused on transforming ECG signals into time-frequency representations. Houssein et al. [15] employed wavelet transform-based feature extraction combined with Manta Ray Foraging Optimization (MRFO) for arrhythmia classification, while Madan et al. [16] utilized CWT scalograms with a CNN–LSTM architecture for automatic arrhythmia recognition. Acharya et al. [17] demonstrated the effectiveness of CNNs for myocardial infarction detection, achieving an accuracy of 95.22%. More recently, Xiao et al. [18] reported that classification performance often decreases under inter-patient evaluation settings, whereas Qiu et al. [19] and Ikram et al. [20] improved classification accuracy using transformer-based architectures and CWT representations.

Despite these advances, challenges such as signal noise, patient variability, limited labeled data, and computational complexity continue to hinder real-world deployment. To address these limitations, this study proposes a hybrid framework that combines CNN-based feature extraction with Multiverse Optimizer (MVO) feature selection and support vector machine (SVM) classification for accurate discrimination between normal and abnormal ECG signals.

3 MATERIAL AND METHODOLOGY

This study aims to increase the success rates by selecting the features obtained with CNN using the metaheuristic algorithm using scalogram and spectrogram images. QTDB was used in our study. Scalogram and spectrogram images were obtained from the ECG signals records in this database. Feature extraction was performed from these images with the created CNN model, and feature selection was made using the MVO algorithm then fed it to SVM for classification. Finally, classification accuracies before and after feature selection were compared.

3.1 Dataset description

We used the QT database (QTDB) from the PhysioNet repository [21], which contains 105 ECG recordings with diverse QRS and ST–T morphologies collected from multiple established databases. In this study, 28 recordings were selected by taking the first four records from each available class in order to balance the dataset, since the smallest class contained only four records. This ensured equal representation across classes and consistency in the experimental setup. The dataset is organized into data and label fields, where data field forms a 28 × 224,999 matrix sampled at 250 Hz, and the corresponding class labels are provided in label field, as summarized in Table 1.

Table 1. Distribution ECG signal across seven classes in the QTDB

Row Index Range	Records IDs	Class Name	Class Label	Records Number
1–4	sel100, sel102, sel103, sel104	MIT-BIH Arrhythmia	ARR	sel100, sel102, sel103, sel104
5–8	sel301, sel302, sel306, sel307	MIT-BIH ST Change	ST	sel301, sel302, sel306, sel307
9–12	sel803, sel808, sel811, sel820	MIT-BIH Supraventricular Arrhythmia	SVT	sel803, sel808, sel811, sel820
13–16	sel0104, sel0106, sel0107, sel0110	European ST-T	ESC	sel0104, sel0106, sel0107, sel0110
17–20	sel14046, sel14157, sel14172, sel15814	MIT-BIH Long-Term ECG	LTA	sel14046, sel14157, sel14172, sel15814
21–24	sel16265, sel16272, sel16273, sel16420	MIT-BIH Normal Sinus Rhythm	NSR	sel16265, sel16272, sel16273, sel16420
25–28	sel30, sel31, sel32, sel33	BIH Sudden Death	SCD	sel30, sel31, sel32, sel33

3.2 Data preprocessing

The preparation of data for testing and training is done at this step. Initially, a converted data store and the resize data helper function are used to segment the data. Furthermore, 1-D ECG signals were converted into 2-D colorful scalogram and spectrogram images using Continuous Wavelet Transformation (CWT) for scalogram, while spectrogram images were created using Short-Time Fourier Transform (STFT).

Data segmentation. Deep learning models such as CNNs require sufficient training data; however, very long ECG recordings may increase computational cost and lead to overfitting. Therefore, the QTDB, which contains 105 ECG records, was utilized in this study, and each record (224,999 samples) was divided into 375 non-overlapping segments of 500 samples (extra samples were discarded). To maintain class balance, four recordings were selected from each ECG class, resulting in 28 records and a total of 10,500 segments. The dataset was split into 80% for training and validation (8,400 segments) and 20% for testing (2,100 segments).

Training, validation, and testing strategy. The generated ECG images were divided into training, validation, and testing sets, comprising 72% (7,560 images), 8% (840 images), and 20% (2,100 images), respectively. Where the testing set contained unseen samples that were not used during model training the model was trained and performed using the SGDM optimizer with a learning rate of 0.0001, mini-batch size of 16, and 35 epochs. During training, validation was carried out at a frequency of 10 iterations to monitor performance and reduce overfitting. The final evaluation was reported using accuracy, precision, recall, F1-score, specificity, and confusion matrix.

Spectrogram and scalogram images. Traditional ECG classification methods often rely on one-dimensional signals that are sensitive to noise and require extensive preprocessing [22]. In this study, ECG segments were transformed into two-dimensional color spectrograms and scalograms to provide richer time–frequency information [23]. Spectrograms were generated using the Short-Time Fourier Transform (STFT) [24], while scalograms were obtained using the Continuous Wavelet Transform (CWT) [25–27], which is well suited for analyzing non-stationary

ECG signals. Both image types were resized to 227 × 227 × 3 to match the CNN input requirements. Examples of the generated images are shown in Figure 1.

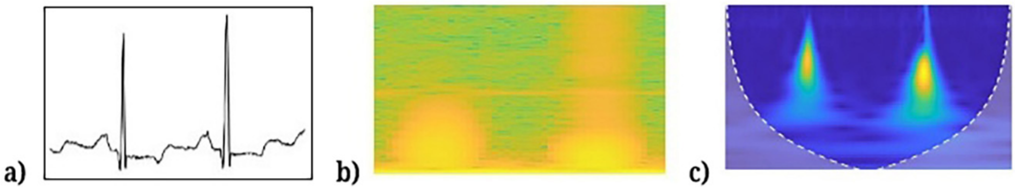


Fig. 1. Sample Arrhythmia (ARR) images from the database
(a) 1D ECG segment (b) spectrogram (c) scalogram

3.3 Proposed method

The proposed framework integrates a CNN for deep feature extraction, the Multiverse Optimizer for feature selection, and a SVM for final classification, as illustrated in Figure 2. The CNN automatically learns discriminative representations from ECG time–frequency images, while MVO removes redundant features and selects the most informative subset. The selected features are then provided to the SVM to achieve robust multi-class classification.

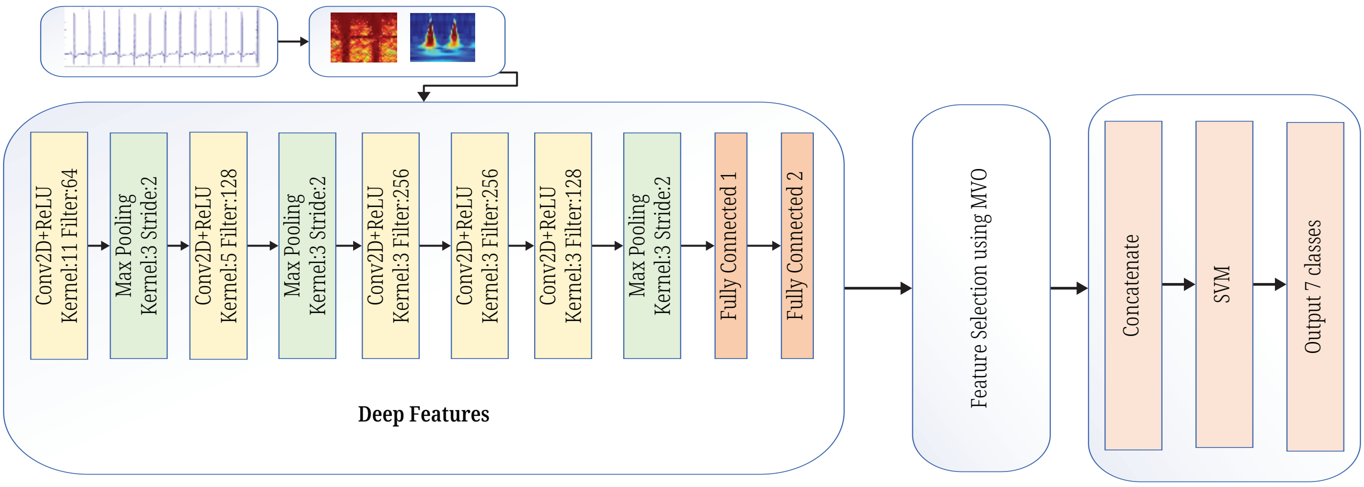


Fig. 2. System architecture method combining CNN, MVO, and SVM

Adopted CNN architecture consists of five convolutional layers, three max-pooling layers, and a flattening layer for feature vector generation. Spectrogram and scalogram images are resized to 227 × 227 pixels before being fed into the network. The first convolutional layer employs 64 filters (kernel size 11 × 11, stride 4 × 4) followed by ReLU activation and a 3 × 3 max-pooling layer with stride 2. The second layer uses 128 filters (stride 1) followed by ReLU and max-pooling (3 × 3, stride 2). The third and fourth layers apply 256 filters each, while the fifth layer uses 128 filters, with ReLU activation in all convolutional layers. Finally, a third max-pooling layer (3 × 3, stride 2) is applied and the resulting feature maps are flattened to produce the deep feature vector. This hybrid CNN+MVO+SVM structure combines the advantages of deep feature learning, metaheuristic feature selection, and margin-based classification. Compared with Genetic Algorithms (GA), MVO provides an effective balance between exploration and exploitation, enabling improved feature subset selection.

To reduce overfitting and enhance generalization, dropout (0.5) and normalization were applied, and the training settings are summarized in Table 2.

Table 2. Parameter tuning of proposed model

Component	Parameter	Value
CNN Input	Image size	$227 \times 227 \times 3$
CNN Architecture	Convolution filters(Conv1-Conv5)	64, 128, 256, 256, 128
CNN Architecture	Filter sizes	11×11 (Conv1), 5×5 (Conv2), 3×3 (Conv3–Conv5)
Pooling	Pool size/Stride	$3 \times 3/2$
Activation	Function	ReLU
Fully Connected Layers	Neurons	512, 512
Dropout	Rate	0.5
Training	Optimizer	SGDM
Training	Learning rate	0.0001
Training	Mini-batch size	16
Training	Epochs	35
Feature Extraction	Layer	FC7

3.4 Algorithm of the proposed framework

To ensure clarity and reproducibility, the complete procedure of the proposed hybrid CNN+MVO+SVM framework is summarized in Algorithm 1. The workflow includes ECG segmentation, time–frequency image generation, deep feature extraction, feature selection, and final classification.

Algorithm 1: Proposed CNN+MVO+SVM Classification

Input: QTDB ECG recordings (28 records, 7 classes $\times$ 4 records).
Output: Predicted ECG class label (7 classes).
1. **Load data:** Import ECG signals and labels from QTDB.
2. **Segmentation:** Split each record (224,999 samples) into 375 non-overlapping segments of 500 samples (total = 10,500 segments).
3. **Time–frequency images:** For each segment, generate:
   - **Spectrogram (STFT):** window = 64, overlap = 60, NFFT = 128, fs = 250 Hz.
   - **Scalogram (CWT):** $|\mathrm{CWT}|$ using MATLAB CWT filter bank. Resize all images to $227 \times 227 \times 3$.
4. **CNN feature extraction:** Train the CNN using SGDM (lr = 0.0001, batch = 16, epochs = 35, dropout = 0.5) and extract deep features from the flatten layer.
5. **Feature selection (MVO):** Apply binary MVO (population = 10, iterations = 30; WEP: 0.2→1.0, p = 6) to select the most informative features.
6. **Classification:** Train a multi-class SVM using the selected features and predict the ECG classes.
7. **Evaluation:** Report accuracy, sensitivity, specificity, F1-score, and confusion matrix.

In the next section, the proposed framework is evaluated using spectrogram and scalogram representations. First, CNN feature extraction performance is analyzed. Next, the effect of MVO-based feature selection and SVM classification is examined. Finally, proposed method is compared with existing studies to highlight its effectiveness.

3.5 Multi verse optimizer

Multiverse optimization (MVO) is a population-based metaheuristic inspired by cosmological concepts to solve optimization problems. In MVO, each universe represents a candidate solution, and the search process is guided by three mechanisms: white holes, black holes and wormholes. White and black holes support global exploration by exchanging features between universes, while wormholes enhance exploitation by moving solutions toward the best universe. Through these interactions, MVO effectively balances exploration and exploitation to identify an optimal solution, as illustrated in Figure 3 [28], [29], [30].

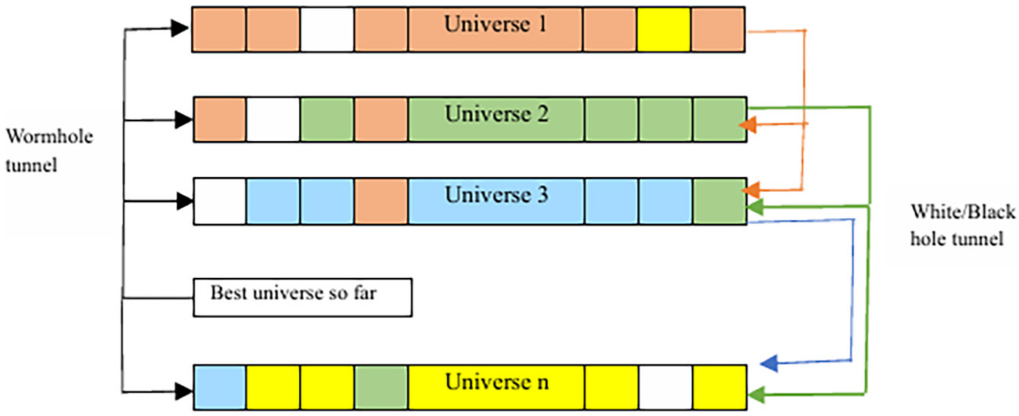


Fig. 3. Concepts of cosmology implemented in MVO algorithm

In the algorithm, the term *universe* refers to candidate solution, represented mathematically as a matrix (1). Here, U is the population of universes with size $n \times d$.

$$U = \begin{bmatrix} x_1^1 & x_1^2 & \cdots & x_1^d \\ x_2^1 & x_2^2 & & x_2^d \\ \vdots & & \ddots & \vdots \\ x_n^1 & x_n^2 & \cdots & x_n^d \end{bmatrix} \tag{1}$$

Two parameters, WEP and TDR, are calculated to update the solutions. They regulate the update frequency and step size, and are defined as follows [28]:

$$WEP = a + t * \left(\frac{b-a}{T}\right) \tag{2}$$

a: minimum, b: maximum, t: current iteration, T: maximum iterations.

$$TDR = 1 - \frac{t^{\frac{1}{p}}}{T^{\frac{1}{p}}} \tag{3}$$

The key TDR parameter is p, which controls the level of exploitation. After computing WEP and TDR, the solution positions are updated using the following equation:

$$x_i^j = \begin{cases} \begin{cases} x_j + TDR + ((ub_j - lb_j) * r_4 + lb_j) & if\ r_3 < 0.5 \\ x_j - TDR + ((ub_j - lb_j) * r_4 + lb_j) & if\ r_3 \geq 0.5 \end{cases} & if\ r_2 < WE \\ x^j_{Roulette\ Wheel} & if\ r_2 \geq WEP \end{cases} \tag{4}$$

Here, x_j is the j-th element of the best solution. lb_j and ub_j are the lower and upper bounds, and $r_2, r_3, r_4 \in [0,1]$ are random numbers. x_i^j denotes the j-th parameter of the i-th solution, while x_{RW}^j is selected using roulette wheel selection. In our experiments, $WEP_{min} = 0.2$ and $WEP_{max} = 1$. Figure 4 illustrates the MVO flowchart.

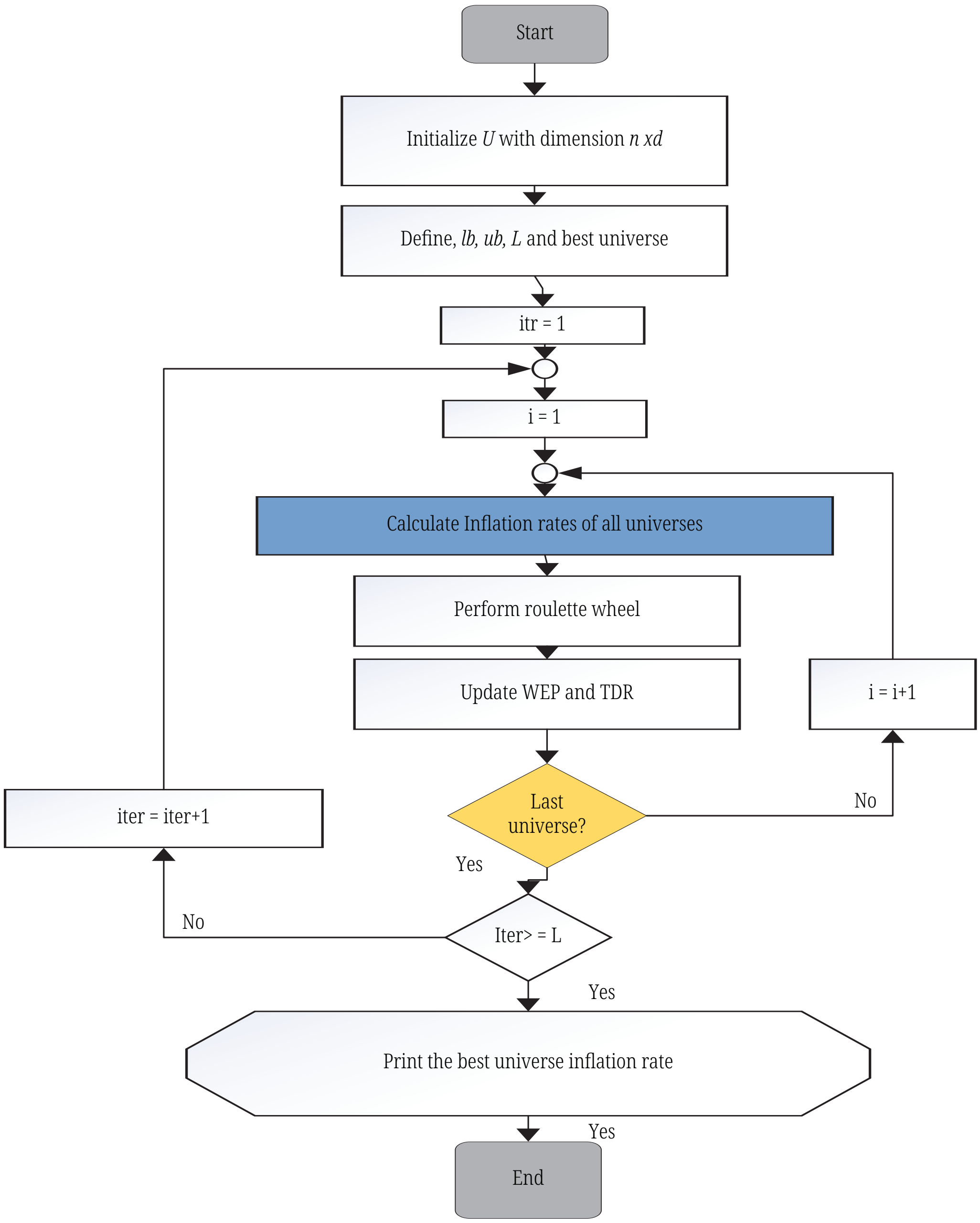


Fig. 4. MVO algorithm flowchart representation

3.6 Multiclass support vector machine

The SVM was initially a binary classifier that used training data to select the best hyperplane for classifying unknown data into two groups. A finite number of hyperplanes can be established in SVM, and the hyperplane is placed at the distance where the nearest points of the two classes are separated by a maximum value known as the margin. SVM selects the maximum one, though. Let X be the following: ($x1$, $y1$), ($x2$, $y2$), …, (xm, ym), where xi, $i \in \{1, 2, 3, …, m\}$ belong to the training set and yi represent their labels as $yi \in \{1, -1\}$, Figure 5 displays the perfect SVM. Equation 5 provides an equation for the separating hyperplane.

$$W \cdot xi + b = 0 \tag{5}$$

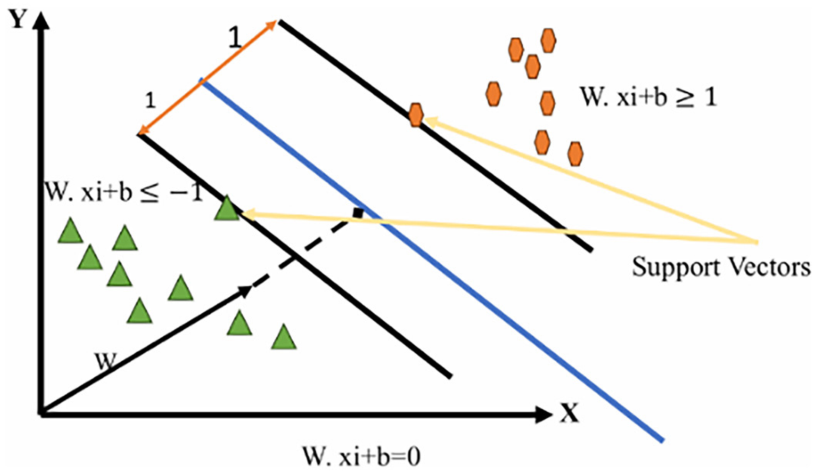


Fig. 5. Conceptual of SVM classification boundary

The SVM classifies samples using a decision function based on feature weights and a bias term, while maximizing the margin between classes. For multi-class problems, the classification task is decomposed into multiple binary classifications. In this study, a one-versus-one strategy with a linear kernel function was employed for multi-class ECG classification [31].

4 EXPERIMENTAL RESULTS

The proposed model was implemented in MATLAB R2021b on a system with an Intel Core i7 processor, 32 GB RAM, and an NVIDIA GPU. CNN training, MVO-based feature selection, and SVM classification were performed using spectrogram and scalogram images from the QTDB dataset.

4.1 Performance metrics

The effectiveness of the proposed model was quantified using confusion-matrix-based indicators that are broadly recognized in classification research [32]. Overall correctness was measured by accuracy, defined as

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{6}$$

- The reliability of positive predictions was determined using precision

$$Precision = \frac{TP}{TP + FP} \tag{7}$$

- Recall measured the detection rate of actual positive samples.

$$Recall = \frac{TP}{TP + FN} \tag{8}$$

- Specificity measured the model's ability to correctly reject negative cases.

$$Specificity = \frac{TN}{TN + FP} \tag{9}$$

- The F1-score was used to measure the balance between precision and recall.

$$F1 - score = \frac{2 * recall * precision}{recall + precision} \tag{10}$$

where TP, TN, FP, and FN denote true positives, true negatives, false positives, and false negatives, respectively. The classifier performance was further evaluated using ROC curves and the corresponding AUC values, where higher AUC indicates better class separability.

$$AUC = \frac{1}{2}\left(\frac{TP}{TP + FN} + \frac{TN}{TN + FP}\right) \tag{11}$$

4.2 Evaluation of the proposed method

This study evaluated the effectiveness of MVO-based feature selection and SVM classification using deep features extracted by a CNN from ECG scalogram and spectrogram images generated from the QTDB dataset. The CNN initially extracted 512 deep features, which were subsequently reduced to 259 informative features using the MVO algorithm. The selected features were then classified into seven ECG classes using SVM. As presented in Tables 3–6, the proposed CNN+MVO+SVM framework consistently outperformed the standalone CNN model, with the highest classification performance achieved using scalogram-based representations.

Table 3. Comparison of ECG classification efficiency using CNN-based feature extraction with scalogram representations (512 Features) in QTDB

Class No.	Precision (%)	Recall (%)	Specificity (%)	F1-Score (%)
ARR	99.66	99.00	99.21	99.33
ESC	100.00	99.33	99.89	99.67
LTA	99.66	97.00	97.90	98.31
NSR	99.00	98.67	100.00	98.83
SCD	95.21	99.33	99.49	97.23
ST	97.97	96.67	97.78	97.32
SVT	96.38	97.67	99.00	97.02
Average	**98.27**	**98.24**	**99.03**	**98.24**

Table 4. Comparison of ECG classification efficiency using CNN-based feature extraction with spectrogram representations (512 Features) in QTDB

Class No.	Precision (%)	Recall (%)	Specificity (%)	F1-Score (%)
ARR	97.39	99.33	99.22	98.35
ESC	99.66	99.00	100.00	99.33
LTA	91.51	97.00	99.00	94.17
NSR	95.02	82.67	97.16	88.41
SCD	71.25	95.00	95.16	81.43
ST	99.27	91.00	99.50	94.96
SVT	88.43	71.33	98.78	78.97
Average	**91.79**	**90.76**	**98.14**	**90.80**

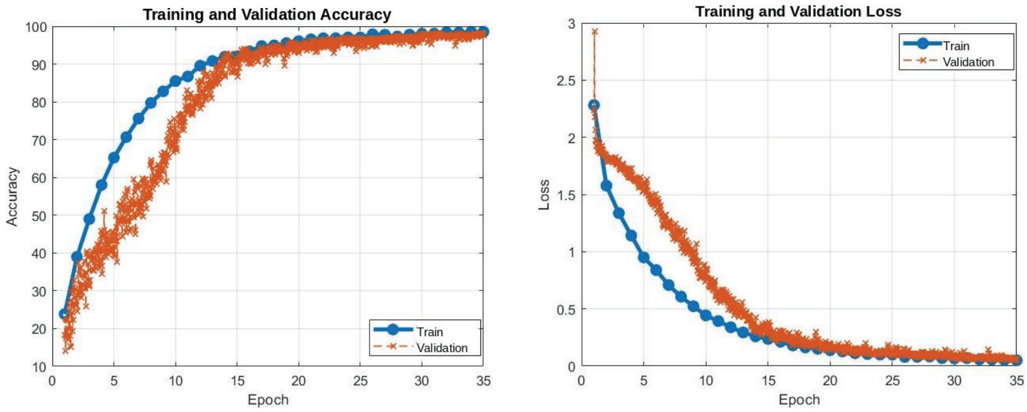
Table 5. Comparison of ECG classification efficiency using hybrid method CNN+MVO+SVM with scalogram representations (259 Features)

Class No.	Precision (%)	Recall (%)	Specificity (%)	F1-Score (%)
ARR	100.00	99.67	100.00	99.83
ESC	100.00	99.33	100.00	99.67
LTA	99.67	99.67	99.94	99.67
NSR	99.67	99.33	99.94	99.50
SCD	99.67	99.67	99.94	99.67
ST	98.33	98.00	99.72	98.16
SVT	97.70	99.33	99.61	98.51
Average	**99.29**	**99.29**	**99.88**	**99.29**

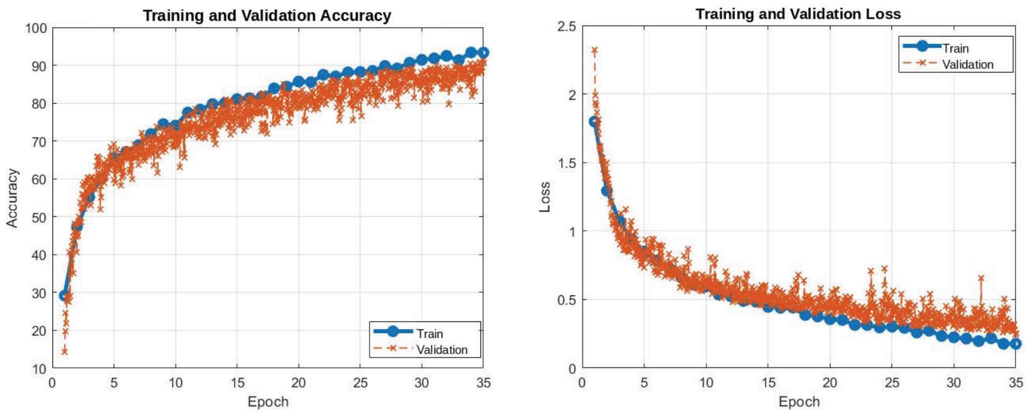
Table 6. Comparison of ECG classification efficiency using hybrid method CNN+MVO+SVM with spectrogram representations (259 Features)

Class No.	Precision (%)	Recall (%)	Specificity (%)	F1-Score (%)
ARR	98.65	97.67	99.44	98.16
ESC	99.33	99.33	100.00	99.33
LTA	94.50	97.33	99.00	95.89
NSR	92.14	86.00	97.17	88.97
SCD	73.80	92.00	95.17	81.90
ST	96.61	95.00	99.56	95.80
SVT	89.80	73.33	98.78	80.73
Average	**92.12**	**91.52**	**98.44**	**91.54**

In Table 6 the relatively lower performance observed for the SCD class can be attributed to several factors. First, morphological similarities between SCD and other ECG classes in the spectrogram domain may reduce class separability. Second, spectrogram representations may not fully capture discriminative frequency-domain characteristics specific to this class. In addition, class imbalance and intra-class variability can further affect the model's ability to learn robust SCD-specific features. These limitations suggest that future improvements could be achieved by incorporating advanced data augmentation strategies, utilizing larger and more balanced datasets, and exploring alternative time–frequency representations that may better preserve class-specific patterns for SCD detection. To further assess robustness, statistical analysis was performed over 20 independent runs. The CNN+MVO model achieved 98.16% ± 0.10, while the proposed CNN+MVO+SVM reached 99.28% ± 0.14. A paired t-test confirmed that the improvement is statistically significant ($p < 0.0001$), demonstrating the effectiveness of the proposed framework. As shown in Figure 6, both spectrogram and scalogram representations improve performance on the QTDB dataset; however, scalogram features yield higher accuracy due to their stronger representation of ECG time–frequency characteristics. It is also important to note that CNN and CNN+MVO+SVM represent different approaches. CNN performs end-to-end classification, whereas the proposed method uses CNN as a feature extractor followed by MVO-based feature selection and SVM classification. Therefore, results are reported separately for a fair comparison between deep learning and hybrid machine learning approaches.

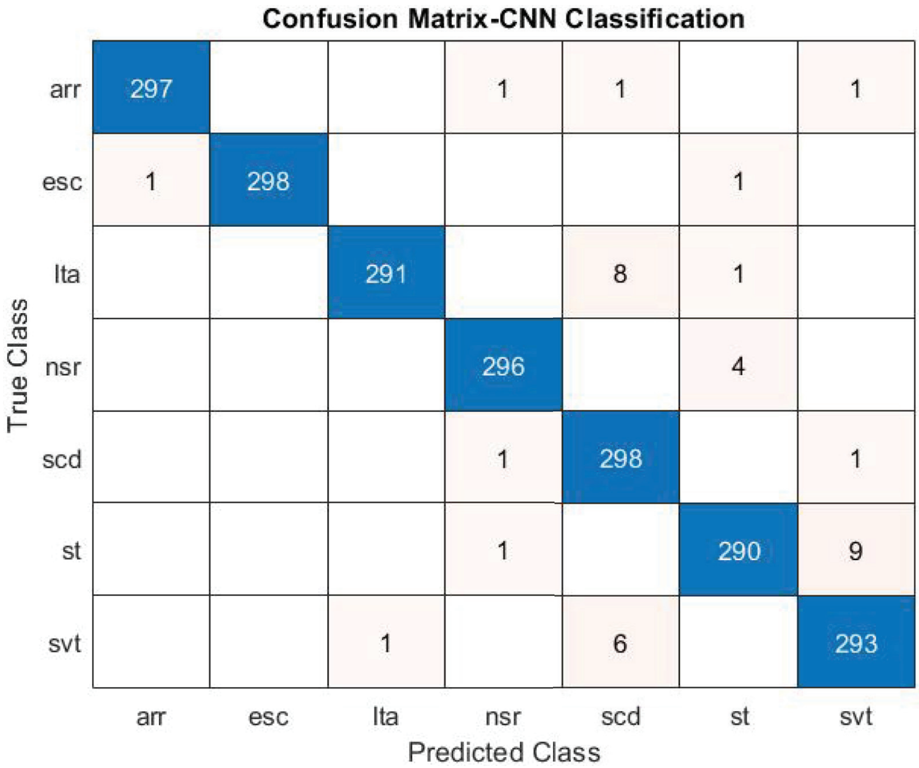


a) Scalogram + CNN

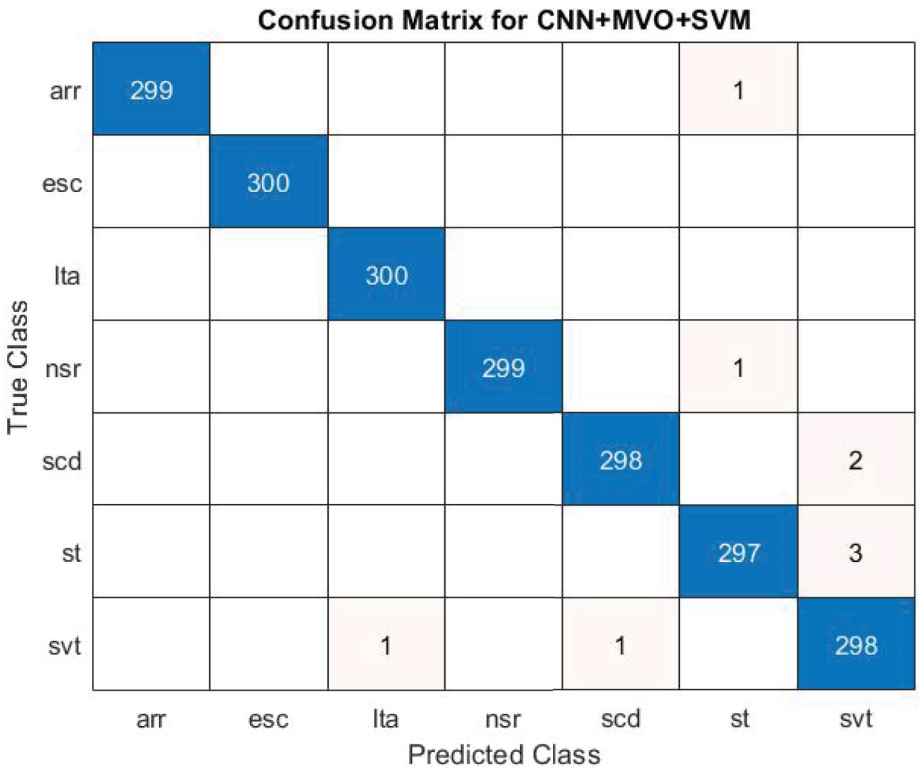


b) Spectrogram + CNN

Fig. 6. CNN performance comparison of the CNN model for ECG classification using scalogram and spectrogram representations

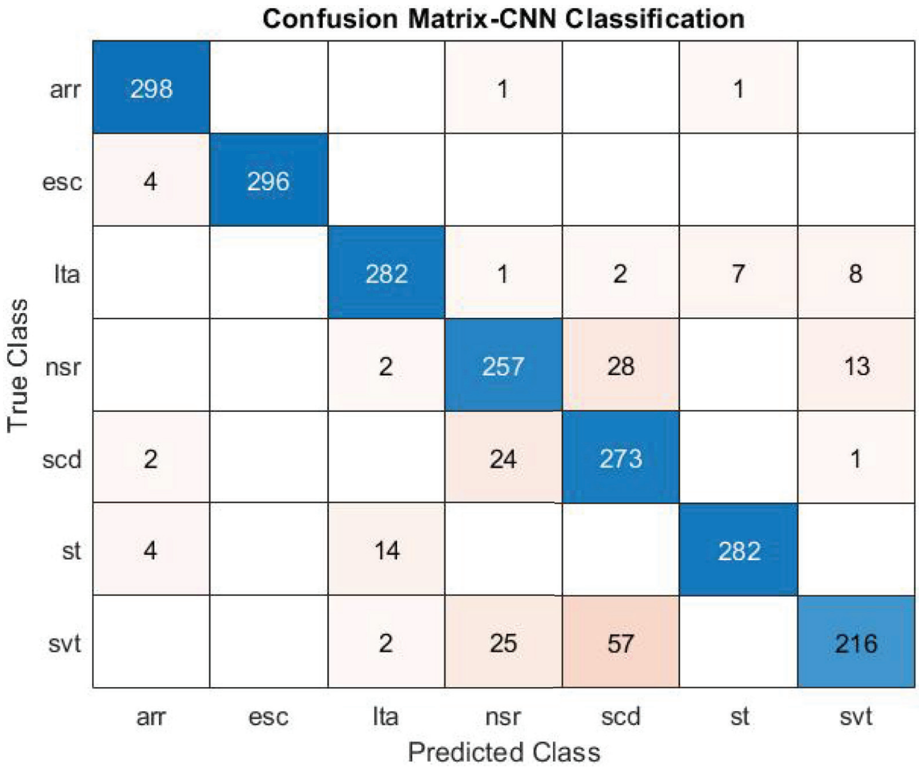


a) Scalogram + CNN

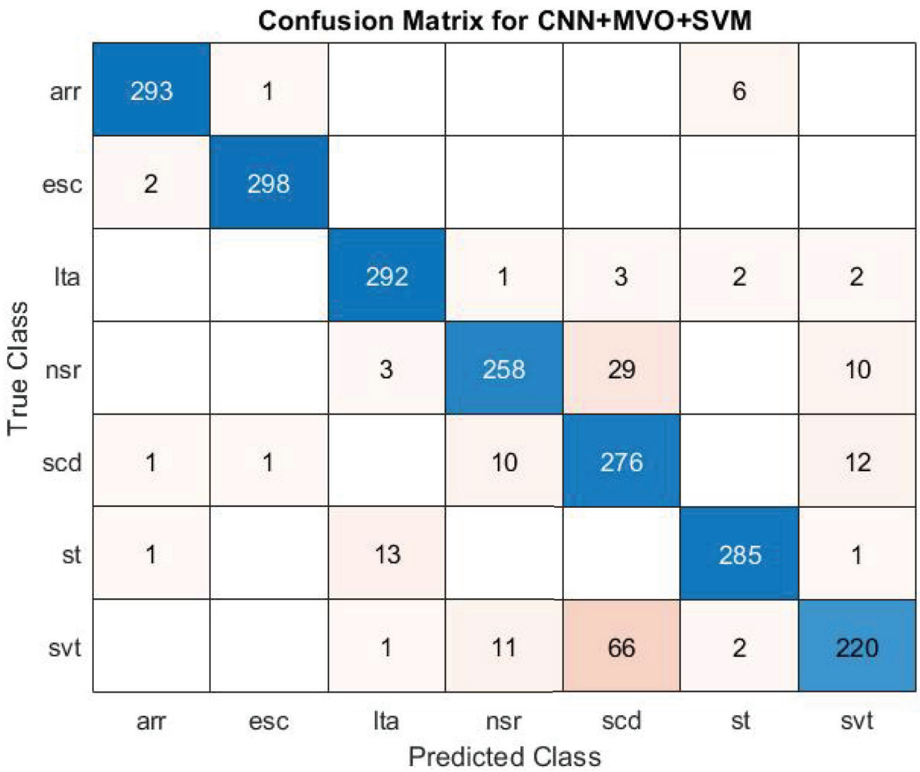


b) Scalogram + CNN+MVO+SVM

Fig. 7. *(Continued)*



c) Spectrogram + CNN



d) Spectrogram + CNN+MVO+SVM

Fig. 7. Confusion matrix of ECG classification results for scalogram and spectrogram representations using both the CNN model and the proposed CNN+MVO+SVM framework

Figure 7 shows that the proposed method provided the greatest improvement for the ARR and LTA classes in scalogram images and for the ESC class in spectrogram images. Additionally, the ROC curves in Figure 8 demonstrate that scalogram representations achieved higher AUC values and superior classification performance than spectrograms.

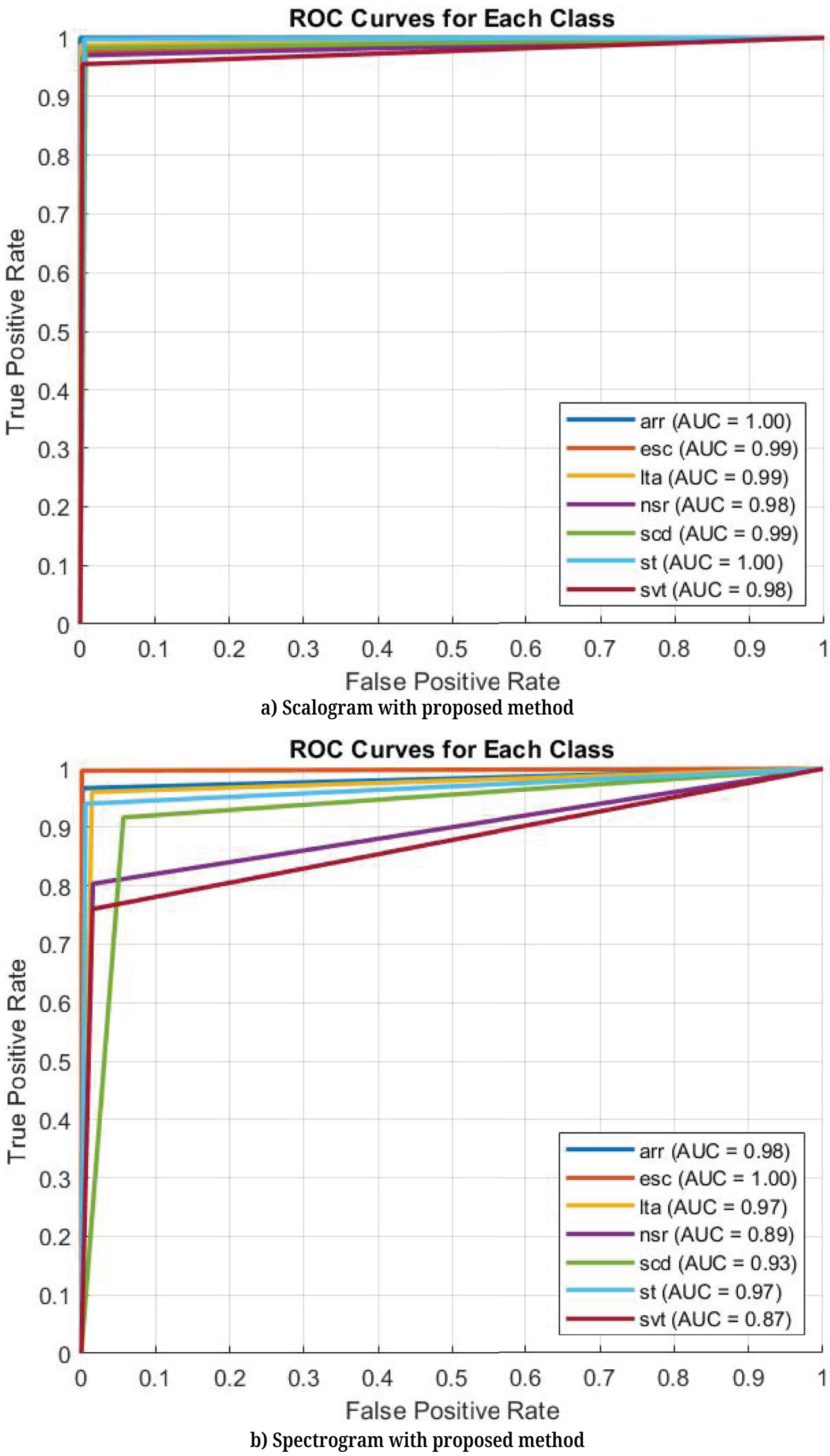


Fig. 8. ROC curve of the both scalogram and spectrogram using proposed method for classification QTDB

4.3 Generalization evaluation (unseen testing samples)

To evaluate performance on unseen data, four QTDB records were selected per class and segmented into fixed-length windows. An 80% and 20% split was applied within each record, where 80% of segments were used for training and 20% were reserved as unseen test data. Under this setting, CNN+SVM achieved 98.16% ± 0.10, while the proposed CNN+MVO+SVM achieved 99.28% ± 0.14. Although the proposed model demonstrated stable performance across 20 independent runs, the present study relies on a fixed 80/20 train–test partition. Future work will investigate more rigorous validation strategies, such as k-fold cross-validation and cross-database evaluation, to further assess the robustness and generalization capability of the proposed framework.

4.4 Comparative analysis with related studies

To evaluate the effectiveness of the proposed framework, its performance was compared with representative ECG classification methods reported in the literature, as summarized in Table 7. Despite differences in datasets and experimental settings, which limit direct benchmarking, the proposed approach achieved competitive results. Unlike many existing methods that rely on deeper network architectures, the proposed framework integrates CNN-based feature extraction, MVO-based feature selection, and SVM classification to achieve high classification performance with a relatively simple architecture.

Table 7. Comparison of the obtained results with related studies

Author	Input Image/Features Extraction	Database	Model Architecture	Accuracy	Sensitivity	Specificity
Noman *et al.* [5]	Spectrogram/ Raw(norm-dur)+MFCC	CinC Challenge 2016 Heart Sound	ECNN	89.22%	89.94%	86.35%
Zabihi *et al.* [8]	Raw ECG (1D signal)	MIT-BIH arrhythmia	ResNet+LSTM	99.26%	96.03%	–
Karthiga & Abriami [10]	DWT feature vector	MIT-BIH arrhythmia	CNN	91.92%	90.21%	95.18%
Ahmed *et al.* [11]	Scalogram/CNN	ECG Images dataset	GoogleNet+SVM	96.58%	96.58%	–
Londhe & Atulkar [13]	Scalogram/CNN	QTDB	CNN+LSTM	96.88%	–	88.69%
Houssein *et al.* [15]	Scalogram/LBP, HOS, and RR intervals	MIT-BIH arrhythmia	MRFO+SVM	97.86%	97.88%	99.35%
Madan *et al.* [16]	Scalogram/CNN	QTDB	CNN-LSTM	98.90%	98.33%	98.35%
Acharya *et al.* [17]	Scalogram/ R-Peak	MIT-BIH arrhythmia	11-layer CNN	96.00%	95.49%	94.19%
Bhekumuzi *et al.* [22]	Scalogram/ images using 2D recurrent plots	MIT-BIH Atrial MIT-BIH Malignant	CNN	95.30%	94.20%	95.00%
Zheng *et al.* [23]	Scalogram/CNN	MIT-BIH arrhythmia	CNN-LSTM	99.01%	97.67%	99.57%
Proposed Method	**Scalogram**	**QTDB**	**CNN+MVO+SVM**	**99.29%**	**99.29%**	**99.88%**
	Spectrogram			**92.12%**	**91.52%**	**98.44%**

The proposed CNN contains five convolutional layers, three max-pooling layers, and two fully connected layers, providing an effective balance between feature learning capability and model simplicity. As a result, approximately 50% of the extracted features were removed during the optimization stage, reducing feature redundancy and improving the quality of the selected feature subset. This feature reduction also supports better generalization by limiting unnecessary information in the final feature space. Although some published studies achieve high accuracy using more complex architectures, the results in Table 7 indicate that the proposed hybrid framework can achieve comparable or superior classification performance. By combining CNN-based feature extraction, MVO-based feature selection, and SVM classification, the proposed method provides an effective approach for ECG signal classification.

5 CONCLUSION

Reducing unnecessary data in data sets plays an important role in increasing the ECG signals success rate. This article aims to improve the success rates by selecting the features obtained with CNN using the metaheuristic algorithm using scalogram and spectrogram images. We designed a CNN model comprising five convolutional layers, three max-pooling layers, and two fully connected layers. Performance and effectiveness of model were tested using QTDB. Scalogram and spectrogram images obtained from digitized ECG signals recordings available in this database. By applying these obtained images to the designed CNN model, feature extraction was carried out, and then feature selection was carried out using the MVO algorithm finally the classify of ECG signals were done by SVM. As a result of the experiments, the proposed method has accuracy of 99.29% and 92.12% in the QTDB in scalogram and spectrogram images, respectively. The number of features was reduced by 50% in both kinds of image. We are planning studies on different hybrid models to increase the success rate further in future studies especially for spectrogram images.

6 ACKNOWLEDGMENT

The support and assistance provided by Duhok Polytechnic University and the University of Duhok are highly appreciated and gratefully acknowledged throughout the completion of this study.

7 REFERENCES

[1] G. Savarese, P. M. Becher, L. H. Lund, P. Seferovic, G. M. C. Rosano, and A. J. S. Coats, "Global burden of heart failure: A comprehensive and updated review of epidemiology," *Cardiovascular Research*, vol. 118, no. 17, pp. 3272–3287, 2022. https://doi.org/10.1093/cvr/cvac013

[2] J. Schläpfer and H. J. Wellens, "Computer-interpreted electrocardiograms: Benefits and limitations," *Journal of the American College of Cardiology*, vol. 70, no. 9, pp. 1183–1189, 2017. https://doi.org/10.1016/j.jacc.2017.07.723

[3] C. J. Zhang, Yuan-Lu, F. Q. Tang, H. P. Cai, Y. F. Qian, and Chao-Wang, "Heart failure classification using deep learning to extract spatiotemporal features from ECG," *BMC Medical Informatics and Decision Making*, vol. 24, no. 1, 2024. https://doi.org/10.1186/s12911-024-02415-4

[4] Y. Ansari, O. Mourad, K. Qaraqe, and E. Serpedin, "Deep learning for ECG arrhythmia detection and classification: Overview of progress for period 2017–2023," *Frontiers in Physiology,* vol. 14, p. 1246746, 2023. https://doi.org/10.3389/fphys.2023.1246746

[5] F. Noman, C. M. Ting, S. H. Salleh, and H. Ombao, "Short-segment heart sound classification using an ensemble of deep convolutional neural networks," in *IEEE ICASSP 2019,* Brighton, UK, 2019, pp. 1318–1322. https://doi.org/10.1109/ICASSP.2019.8682668

[6] S. Hadiyoso, F. Fahrozi, and M. D. Sulistiyo, "Image based ECG signal classification using convolutional neural network," *International Journal of Online & Biomedical Engineering*, vol. 16, no. 4, pp. 64–78, 2022. https://doi.org/10.3991/ijoe.v18i04.27923

[7] M. Jogin, Mohana, M. S. Madhulika, G. D. Divya, R. K. Meghana, and S. Apoorva, "Feature extraction using convolution neural networks and deep learning," in *2018 3rd IEEE International Conference on Recent Trends in Electronics, Information & Communication Technology (RTEICT)*, Bangalore, India, 2018, pp. 2319–2323. https://doi.org/10.1109/RTEICT42901.2018.9012507

[8] F. Zabihi, F. Safara, and B. Ahadzadeh, "An electrocardiogram signal classification using a hybrid machine learning and deep learning approach," *Healthcare Analytics,* vol. 6, p. 100366, 2024. https://doi.org/10.1016/j.health.2024.100366

[9] M. Cao, T. Zhao, Y. Li, W. Zhang, P. Benharash, and R. Ramezani, "ECG heartbeat classification using deep transfer learning with convolutional neural network and STFT technique," *Journal of Physics: Conference Series*, vol. 2547, no. 1, p. 012031, 2023. https://doi.org/10.48550/arXiv.2206.14200

[10] S. Karthiga and A. M. Abirami, "Deep learning convolutional neural network for ECG signal classification aggregated using IoT," *Computer Systems Science and Engineering*, vol. 42, no. 3, pp. 851–866, 2022. https://doi.org/10.32604/csse.2022.021935

[11] M. Ahmad, A. Ahmed, H. Hashim, M. Farsi, and N. Mahmoud, "Enhancing heart disease diagnosis using ECG signal reconstruction and deep transfer learning classification with optional SVM integration," *Diagnostics*, vol. 15, no. 12, p. 1501, 2025. https://doi.org/10.3390/diagnostics15121501

[12] S. L. Oh, E. Y. K. Ng, R. S. Tan, and U. R. Acharya, "Automated diagnosis of arrhythmia using combination of CNN and LSTM techniques with variable-length heartbeats," *Computers in Biology and Medicine*, vol. 102, pp. 278–287, 2018. https://doi.org/10.1016/j.compbiomed.2018.06.002

[13] A. N. Londhe and M. Atulkar, "Semantic segmentation of ECG waves using hybrid channel-mix convolutional and bidirectional LSTM," *Biomedical Signal Processing and Control*, vol. 63, p. 102162, 2021. https://doi.org/10.1016/j.bspc.2020.102162

[14] S. Nurmaini *et al.*, "Electrocardiogram signal classification for automated delineation using bidirectional long short-term memory," *Informatics in Medicine Unlocked*, vol. 22, p. 100507, 2021. https://doi.org/10.1016/j.imu.2020.100507

[15] E. H. Houssein, I. E. Ibrahim, N. Neggaz, M. Hassaballah, and Y. M. Wazery, "An efficient ECG arrhythmia classification method based on Manta ray foraging optimization," *Expert Systems with Applications*, vol. 181, p. 115131, 2021. https://doi.org/10.1016/j.eswa.2021.115131

[16] P. Madan, V. Singh, D. P. Singh, M. Diwakar, B. Pant, and A. Kishor, "A hybrid deep learning approach for ECG-based arrhythmia classification," *Bioengineering*, vol. 9, no. 4, p. 152, 2022. https://doi.org/10.3390/bioengineering9040152

[17] U. R. Acharya, H. Fujita, S. L. Oh, Y. Hagiwara, J. H. Tan, and M. Adam, "A deep convolutional neural network model to classify heartbeats," *Computers in Biology and Medicine*, vol. 89, pp. 389–396, 2017. https://doi.org/10.1016/j.compbiomed.2017.08.022

[18] Q. Xiao, K. Lee, S. A. Mokhtar, and I. Ismail, "Deep learning-based ECG arrhythmia classification: A systematic review," *Applied Sciences*, vol. 13, no. 8, p. 4964, 2023. https://doi.org/10.3390/app13084964

[19] C. Qiu, H. Li, C. Qi, and B. Li, "Enhancing ECG classification with continuous wavelet transform and multi-branch transformer," *Heliyon*, vol. 10, no. 5, p. e26147, 2024. https://doi.org/10.1016/j.heliyon.2024.e26147

[20] S. Ikram *et al.*, "Transformer-based ECG classification for early detection of cardiac arrhythmias," *Frontiers in Medicine*, vol. 12, 2025. https://doi.org/10.3389/fmed.2025.1600855

[21] P. Laguna, R. G. Mark, A. Goldberg, and G. B. Moody, "Database for evaluation of algorithms for measurement of QT and other waveform intervals in the ECG," *Computers in Cardiology*, pp. 673–676, 1997. https://doi.org/10.1109/CIC.1997.648140

[22] B. M. Mathunjwa, Y. T. Lin, C. H. Lin, M. F. Abbod, and J. S. Shieh, "ECG arrhythmia classification by using a recurrence plot and convolutional neural network," *Biomedical Signal Processing and Control*, vol. 64, p. 102262, 2021. https://doi.org/10.1016/j.bspc.2020.102262

[23] Z. Zheng, Z. Chen, F. Hu, J. Zhu, Q. Tang, and Y. Liang, "Automatic diagnosis of arrhythmias using a combination of CNN and LSTM technology," *Electronics*, vol. 9, no. 1, 2020. https://doi.org/10.3390/electronics9010121

[24] A. Eleyan, F. Bayram, and G. Eleyan, "Spectrogram-based arrhythmia classification using three-channel deep learning model with feature fusion," *Applied Sciences*, vol. 14, no. 21, 2024. https://doi.org/10.3390/app14219936

[25] Y. Zhao, J. Cheng, P. Zhang, and X. Peng, "ECG classification using deep CNN improved by wavelet transform," *Computers, Materials & Continua*, vol. 64, no. 3, pp. 1615–1628, 2020. https://doi.org/10.32604/cmc.2020.09938

[26] M. R. Fikri, I. Soesanti, and H. A. Nugroho, "ECG signal classification review," *IJITEE (International Journal of Information Technology and Electrical Engineering)*, vol. 5, no. 1, pp. 15–20, 2021. https://doi.org/10.22146/ijitee.60295

[27] S. C. Mohonta, M. A. Motin, and D. K. Kumar, "Electrocardiogram-based arrhythmia classification using wavelet transform with deep learning model," *Sensors and Biosensing Research*, vol. 37, 2022. https://doi.org/10.1016/j.sbsr.2022.100502

[28] L. Amezquita, O. Castillo, J. Soria, and P. Cortes-Antonio, "New variants of the multi-verse optimizer algorithm adapting chaos theory in benchmark optimization," *Symmetry*, vol. 15, no. 7, 2023. https://doi.org/10.3390/sym15071319

[29] O. Yılmaz, A. A. Altun, and M. Köklü, "Optimizing the learning process of multilayer perceptrons using a hybrid algorithm based on MVO and SA," *International Journal of Industrial Engineering Computations*, vol. 13, no. 4, pp. 617–640, 2022. https://doi.org/10.5267/j.ijiec.2022.5.003

[30] F. M. Behbahani *et al.*, "Multi-objective multiverse optimization for optimal allocation of distributed generators and battery energy storage systems: The optimal parallel processing schemes," *Electric Power Systems Research*, vol. 231, p. 110298, 2024. https://doi.org/10.1016/j.epsr.2024.110298

[31] Z. C. Oleiwi, E. N. AlShemmary, and S. Al-Augby, "Arrhythmia detection based on new multi-model technique for ECG inter-patient classification," *International Journal of Online & Biomedical Engineering*, vol. 19, no. 12, pp. 78–98, 2023. https://doi.org/10.3991/ijoe.v19i12.41631

[32] S. I. Safie, N. H. Ja'afar, A. Johari, and M. A. Ismail, "ECG biometric authentication using deep CNN feature learning from analytic wavelet-transformed signals," *International Journal of Online & Biomedical Engineering*, vol. 20, no. 15, pp. 4–18, 2024. https://doi.org/10.3991/ijoe.v20i15.51041

8 AUTHORS

Shelan K. Ahmed is a Lecturer in the Energy Engineering Department at Duhok Polytechnic University, Kurdistan Region, Iraq. She received her B.Sc. (2006) from the University of Mosul and M.Sc. (2014) from Cyprus International University. She is currently a Ph.D. student in Electrical and Computer Engineering at the University of Duhok (E-mail: shelan.kamal@dpu.edu.krd).

Serwan A. Mohammed is a Lecturer in the Electrical and Computer Engineering Department at the University of Duhok, Iraq. He received his B.Sc. (1997) from the University of Baghdad, M.Sc. (2002) from the University of Technology, Baghdad, and Ph.D. from the University of Duhok. His research interests include VLSI and signal processing (E-mail: serwan.mohammed@uod.ac).

Ahmed Kh. Mohammed is a Professor in the Electrical and Computer Engineering Department at the University of Duhok, Iraq. He received his B.Sc. (1977), M.Sc. (1980), and Ph.D. (2003) from the University of Mosul. His research interests include VLSI architectures and signal processing (E-mail: ahmed.khorsheed@uod.ac).