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Optimizing Cubic Spline Control Points *via* Tabu Search for Enhanced ECG Classification Using DNN

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ABSTRACT– The quality of electrocardiogram (ECG) signals plays a crucial role in the performance of deep neural network (DNN) models on cardiac arrhythmia classification. The performance of deep neural network (DNN) models on cardiac arrhythmia classification is highly influenced by the quality of electrocardiogram (ECG) signals. This paper presents a novel optimization-based preprocessing framework CS-TS-DNN that combines Cubic Spline interpolation with Tabu Search (TS) metaheuristic for the automatic selection of optimal spline control points to represent the ECG signal. The proposed model can be used to optimize the data adaptively for improved classification accuracy and signal morphology preservation without employing heuristic approaches to pre-processing. The proposed approach has two stages. ECG signals are normalized and class imbalance is addressed using the Synthetic Minority Oversampling Technique (SMOTE). Second, Cubic Spline interpolation is applied using both manually selected and Tabu Search-optimized spline control points. To search the space of spline-lengths for the optimal configuration, Tabu Search has used 20 iterations. The proposed model has been tested on the Arrhythmia dataset from both INCART and MIT-BIH. The experimental results showed that the TS-based optimization method outperformed the manual spline selection. The proposed model gave an optimal spline length of 19 and achieved 98.75% accuracy on INCART, whereas manual selection resulted in 98.27% accuracy. The second validation on MIT-BIH has 97.75% accuracy with an optimized spline length of 162. The results showed that adaptive preprocessing optimization enhances the quality of representation, classification accuracy, robustness, and generalizability of the ECG across different datasets.

Keywords: Healthcare, ECG, AI, Cubic Spline, DNN, Optimization algorithm.

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1. INTRODUCTION

Cardiovascular diseases (CVDs) have remained the number one cause of death globally and cardiac arrhythmias have a considerable number of sudden cardiac deaths [1]. The correct and prompt detection of arrhythmic events based on the electrocardiogram (ECG) signal is thus important in successful clinical intervention [2]. In recent years, deep learning techniques in particular have been able to achieve remarkable success in computer-aided ECG interpretation, particularly those based on 1D Convolutional Neural Networks (1D-CNNs). The quality and representational faithfulness of the input signals however have a strong dependence on their performance [3]. Raw ECG signals are usually affected by noise; baselines wander as well as morphological anomalies that can drastically reduce the models of precision unless effectively eliminated throughout the preprocessing procedure [4]. One issue with preprocessing of ECG signals is determining the right parameter of signal transformation especially in the application of interpolation methods such as cubic spline [5]. The popularity of cubic spline interpolation is because it can produce a smooth and continuous ECG graph of the individual beats without neglecting any important features of the ECG such as the *P* wave, the QRS complex and the *T* wave [6]. This process is directly related to the number of control points which determine a compromise between over-smoothing and undersmoothing [7]. Although it is important, this parameter is often selected in a heuristic manner usually dependent on the dimensionality of the dataset or an arbitrary round off with no optimization at all [8]. These ad hoc decisions limit the replicability of the model and it is not possible to obtain maximum classification performances [9]. Furthermore, ECG data sets like INCART are imbalanced, with a large number of normal (N) beats compared to clinically relevant abnormal rhythms like supraventricular ectopic beats (SVEB), ventricular ectopic beats (VEB) and fusion (F) beats. Although the bias in favor of the majority classes can be alleviated by using such techniques as Synthetic Minority Oversampling Technique (SMOTE), they are dependent on the quality of the underlying signal representation [10]. The CS-TS-DNN (Cubic Spline-

Optimized Tabu Search- Deep Neural Network) two-step model suggested in this work takes into account these mutually dependent challenges. The first performance base is to select manually the spline control points (10,20,34,50,100) and the optimum manual control points (20 control points) is 98.27% percent accurate. On this basis, we propose a data-driven phase of optimization whereby a Tabu Search (TS) metaheuristic systematically searches the control point space (8-36) to find the configuration which maximizes the classification accuracy. The optimization process was executed for 20 iterations and automatically learns that 19 control points have a better validation accuracy of 98.75% thus showing that fine-grained, non-intuitive parameter values could greatly improve model performance. This additional validation on the MIT-BIH dataset obtained a validation accuracy of 97.75% with an optimized spline length of 162, showing the robustness and generalizability of the proposed model across various ECG signals and datasets.

This proposed work is motivated by the fact that excessive reliance on random preprocessing parameters makes the diagnostic system based on ECG weak and the results generalizable to other patients. Along with a distinct need exists of intelligent, adaptive mechanisms to maximize signal representation to suit downstream learning goals. The existing literatures does not investigate the use of Cubic Spline interpolation as an adaptive preprocessing mechanism for ECG classification, neither does it include the combination of metaheuristic optimization and Cubic spline-based ECG preprocessing. Most of the literature does not pay attention to the effects of preprocessing, rather it is assumed to be a non-learnable step that is fixed and performed without consideration of the effects on the model.

The contributions of the Paper are: 1. Proposes an innovative hybrid Cubic Spline–Tabu Search optimization method for adaptive ECG preprocessing. 2. Proposes automatic selection of optimal spline control points *via* a data-driven mechanism, instead of heuristic manual selection. 3. Shows optimized spline configurations can substantially enhance the classification performance of the ECG on both INCART and MIT-BIH datasets. High validation accuracies of 98.75% and 97.75% are obtained at INCART and MIT-BIH, respectively, by using the proposed CS-TS-DNN framework. 5. Offers empirical data showing that the preprocessing optimization using the metaheuristic approach is an effective means to improve the biomedical signal analysis and arrhythmia classification performed by the deep learning approach.

2. LITERATURE REVIEW

Recent advances in ECG-based arrhythmia classification have demonstrated substantial improvements through the integration of deep learning architectures and advanced signal representation techniques. However, most existing studies primarily focus on classifier design while giving limited attention to adaptive preprocessing optimization and spline-based signal representation. Recent literature has increasingly highlighted the importance of preprocessing quality and ECG morphology preservation for improving downstream deep learning performance.

Spline-based ECG modeling approaches have shown promising capabilities for preserving the morphological characteristics of ECG signals while generating smooth and continuous signal representations. Mishra et al. [11] proposed a hybrid parametric spline approach for ECG signal modeling and demonstrated that spline-based representations improve signal smoothness and waveform fidelity. In another study, Mishra et al. [12] compared parametric B-spline and Hermite cubic spline techniques for ECG signal reconstruction and reported that cubic spline-based methods achieve superior morphology preservation with lower interpolation distortion. Similarly, Böck et al. [13] introduced a variable projection-based ECG beat representation framework for accurate ECG delineation and heartbeat characterization, emphasizing the importance of signal representation quality in biomedical analysis.

Several recent studies further investigated preprocessing and signal enhancement techniques for cardiovascular applications. Wang et al. [14] proposed a heartbeat extraction framework using cubic spline interpolation and adaptive bandpass filtering for continuous-wave radar-based vital sign monitoring, demonstrating the effectiveness of spline interpolation in biomedical signal enhancement. Holanda et al. [15] evaluated preprocessing selection strategies for deep learning-based arrhythmia classification using ECG time-frequency representations and confirmed that preprocessing configurations significantly influence classification performance. Furthermore, Fuadah and Lim [16] presented a comprehensive review of machine learning and deep learning methods for cardiovascular signal analysis using ECG, PCG, and PPG signals, highlighting the growing importance of signal preprocessing and representation techniques in cardiovascular disease classification systems.

Despite these advances, existing studies mainly focus on signal modeling, denoising, or classifier development without considering adaptive optimization of spline control points using metaheuristic algorithms. Most current preprocessing approaches rely on fixed handcrafted parameter configurations that may not generalize effectively across different ECG datasets and signal distributions. To the best of our knowledge, no previous work has investigated the integration of Cubic Spline interpolation with Tabu Search optimization for adaptive ECG preprocessing and deep learning-based arrhythmia classification.

Therefore, the proposed CS-TS-DNN framework addresses an important research gap by introducing a metaheuristic-driven preprocessing optimization strategy capable of automatically determining the optimal spline control point configuration to maximize ECG classification performance while preserving diagnostically important signal morphology. *Table 1*

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summarizes recent related studies in ECG preprocessing, spline-based signal representation, and cardiovascular deep learning applications. *Table 1* represent summary of recent literatures. Our work directly addresses this gap by introducing Tabu Search to autonomously determine the optimal number of control points, thereby bridging signal representation quality with downstream classification accuracy. *Figure 1* shows the proposed model architecture.

Table 1. Summary of recent literatures

Author (Year)	Method	Application	Limitations
Mishra et al. (2024) [11]	Hybrid parametric spline modeling	ECG signal representation and smoothing	Did not include deep learning classification or adaptive optimization
Mishra et al. (2024) [12]	Comparative analysis of B-spline and Hermite cubic spline methods	Accurate ECG signal reconstruction and morphology preservation	No metaheuristic optimization or arrhythmia classification framework
Böck et al. (2021) [13]	Variable projection-based ECG beat representation	ECG delineation and heartbeat characterization	Focused on signal representation without preprocessing optimization
Wang et al. (2025) [14]	Cubic spline interpolation with adaptive bandpass filtering	Heartbeat extraction from CW vital sign radar signals	Focused on heartbeat extraction rather than ECG classification or preprocessing optimization
Holanda et al. (2023) [15]	ECG preprocessing selection using time-frequency representations	Deep learning-based arrhythmia classification	Did not optimize spline interpolation parameters or control points
Fuadah et al. (2025) [16]	Review of ML/DL cardiovascular signal analysis methods	ECG, PCG, and PPG disease classification systems	Review study only without proposing optimization-based preprocessing framework

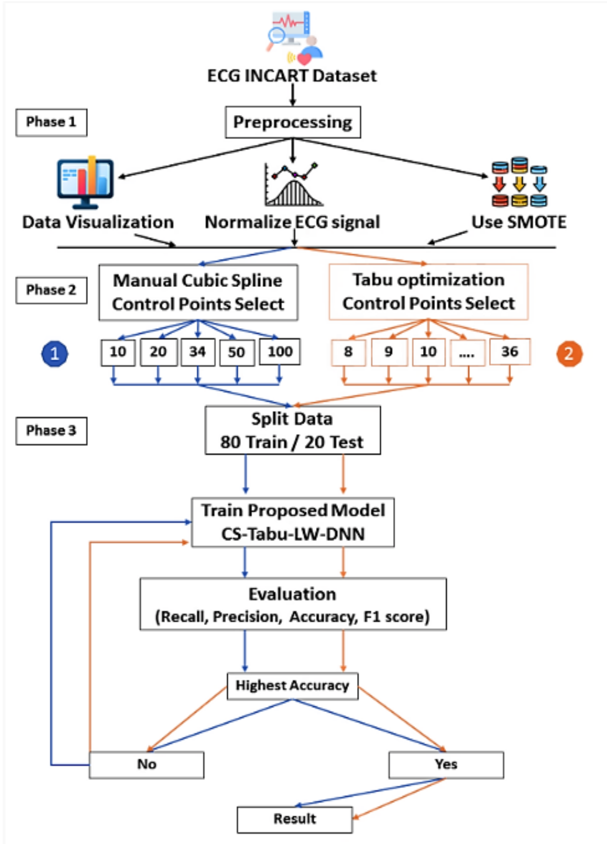

Figure 1. The proposed model architecture

3. PROPOSED METHODOLOGY

3.1. Dataset Description

We use the publicly available ECG dataset INCART and MIT-BIH which consists of ECG recorded from 75 annotated leads. The leads each have heartbeats identified as one of five types: N: Normal beats, VEB: Ventricular Ectopic Beats, SVEB: Supraventricular Ectopic Beats, F: Fusion Beats, Q: Unclassifiable or unknown beats. Each heartbeat is divided into a fixed length window of 34 samples as in the original annotation standard for the INCART and 187 samples for the MIT-BIH. The distribution of the dataset classes for INCART and MIT-BIH shown in *figure 2*. The *figures 2* demonstrate that the datasets are very imbalanced with regard to the classes.

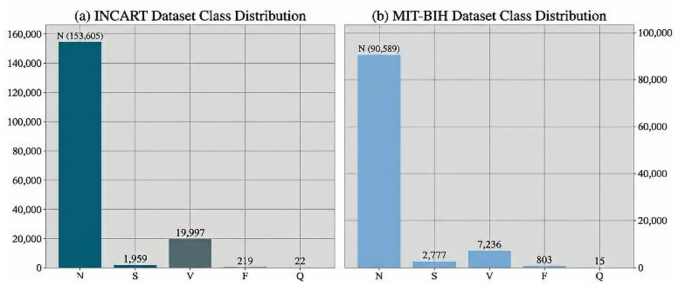

Figure 2. Class distribution of INCART and MIT-BIH dataset

3.1. Signal Preprocessing *via* Cubic Spline

The ECG signals may be noisy, have a drifting baseline, and be morphologically different, which could impact the performance of deep learning-based classification. thus, a suitable pre-processing technique is required to maintain significant ECG features and to enhance the ECG signal representation. Cubic Spline interpolation is used in this work due to its ability to generate smooth and continuous ECG waveforms while preserving diagnostically important features such as the P-wave, QRS complex, and T-wave. Raw ECG segments are first normalized to zero mean and unit variance:

$$x_{norm}(t) = \frac{x(t)-\mu_x}{\sigma_x} \tag{1}$$

$$\mu_x = \frac{1}{T}\sum_{t=1}^{T} x(t) \tag{2}$$

$$\sigma_x = \sqrt{\frac{1}{T}\sum_{t=1}^{T}(x(t)-\mu_x)^2} \tag{3}$$

Where x(t)∈R34 is the original features and T=34 for INCART and for MIT-BIH Where x(t)∈R187 is the original features and T=187.

We apply cubic spline for better signal representing and smoothing without introducing significant signal degradation. Given a set of L control points $\{t_i, x_{norm(t_i)}\}_{\{i=1\}}^{L}$where ti ∈ [1,T] are uniformly spaced, the interpolated signal x^(t) is defined as a piecewise cubic polynomial:

$$\hat{x}(t) = S_i(t) = a_i + b_i(t-t_i) + c_i(t-t_i)^2 + d_i(t-t_i)^3 \tag{4}$$

Subject to continuity constraints on Si(t), Si′(t), and Si′′(t) at interior knots. The output is resampled to a fixed length of 34 points for INCART and 187 points for MIT-BIH points, for compatibility with downstream layers. The parameter L (denoted SPLINE_LENGTH) governs the smoothness-fidelity trade-off: small L oversmooth key features (QRS complex), while large L may overfit noise.

3.1. Class Imbalance Mitigation *via* SMOTE

Cubic spline interpolation combined with the Synthetic Minority Oversampling Technique (SMOTE) is applied to address extreme class imbalance especially for F and Q for both datasets. SMOTE creates synthetic samples on the line segment linking xi to its k-nearest neighbors, xi∈R34 for INCART and xi∈R187 for MIT-BIH, we use k=5 and oversample minority classes to 10% of the number of majority class samples (N). This is only done on the training set to prevent data leakage.

$$x_{new} = x_i + \delta \cdot (x_{nn} - x_i) \tag{5}$$

Where: x_i is the original minority-class sample, x_{nn} is one of its k=5 nearest neighbors, U(0,1) is a uniform distribution between 0 and 1.

3.2. Deep Neural Network Architecture

The proposed model is composed of a fully connected dense layers and dropout regularization, which is effective to learn discriminative features of ECG with low computational complexity. ReLU activation function is used in hidden layers and Softmax activation function in output layer for multi-class classification. The model was trained with Adam optimizer with an adaptive learning rate between 0.001 and 0.000005. For multi-class classification, we used categorical cross-entropy as the loss function:

$$L = -\sum_{c=1}^{5} y_c \log(\hat{y}_c) \tag{6}$$

Where y_c the ground-truth label for class c and $\hat{y}_c$ is the predicted probability, c for total number of classes.

Table 2. The proposed CS-TS-DNN Model Architecture

Layer	Type	Units / Dropout Rate	Activation Function	Trainable Parameters
Input layer	Dense	128	ReLU	4,480
—	Dropout	0.5	—	0
Hidden layer 1	Dense	64	ReLU	8,256
—	Dropout	0.4	—	0
Hidden layer 2	Dense	32	ReLU	2,080
—	Dropout	0.3	—	0
Output layer	Dense	5	Softmax	165

3.3. Tabu Search for Spline Length Optimization

The major contribution of this work is the incorporation of Tabu Search (TS) to find the optimal spline length for an ECG signal representation. The proposed model solves the problem of cubic spline control points selection as an optimization problem which is formulated as the following objective function:

$$L^* = \arg\max_{L \in \mathcal{L}} f(L) \tag{7}$$

where $\mathcal{L}$ represents the spline-length search space.

For the INCART, use a starting solution, L_0=34, which represent the native features of the dataset. And for the MIT-BIH, start with initial solution L_0=187 which represent the native features of the dataset, and the neighborhood structure was defined as:

$$N(L) = \{L-2, L-1, L+1, L+2\} \tag{8}$$

The length of neighboring splines was tested at each iteration, retraining the DNN each time and measuring the accuracy from the validation set. A Tabu List (TL) of size 5 was adopted to avoid re-exploring lengths of splines. Tabu solutions allowed if they yielded a higher global accuracy when validated by the aspiration rule. The stopping criterion was set as either: 20 iterations, or There are no any other non-tabu neighbors that can be considered for the current tabu list, below the algorithm of Tabu search for optimal cubic spline control points (CPs) selection, For MIT-BIH, change only the initial solution to $L_0 =$ 187.

Algorithm 1: Tabu Search for Optimal Cubic Spline CPs Selection

Input: initial solution $L_0 = 34$ *for INCART maximum iterations = 20, Tabu List size = 5*
*Output: Optimal control point value L**
Start
Step1: Initialize the current solution $L_{current}$ 34.
Step2: Evaluate the initial validation accuracy $f(L_{current})$.
Step3: Set the initial best solution as $L^* = L_{current}$
Step4: Initialize an empty Tabu List TL.
Step5: Generate neighboring solutions using:
$N(L) = \{L-2, L-1, L+1, L+2\}$.
Step6: Remove tabu solutions from the neighborhood.
Step7: Evaluate the validation accuracy of each non-tabu neighbor.
Step8: Select the best non-tabu neighbor as the new current solution.
Step9: Update the Tabu List by adding the selected solution and removing the oldest value if the list exceeds size 5.
Step10: If the selected solution improves the best validation accuracy, update L.*
Step11: Repeat Steps 5–10 until 20 iterations are completed or no admissible neighbor remains.
Step12: Return the optimal control point value L.*
End

3.4. Justification for Using Tabu Search

Tabu Search was selected among other metaheuristic optimization algorithms such as Genetic Algorithm (GA), Particle Swarm Optimization (PSO) and Simulated Annealing (SA) due to its low computational complexity, memory-based search mechanism and strong ability to escape local optima in discrete optimization problems. GA and PSO generally need more population and computational cost, while Tabu Search can conduct iterative neighborhood search with a lightweight tabu memory structure, which is more suitable for repeated DNN retraining in spline optimization. Moreover, the optimization problem for spline-length in this work is a discrete integer search space, where Tabu Search offers an efficient convergence with less evaluated solutions than population-based approaches. Thus, TS is a good trade-off between optimization performance and computational efficiency. *Table 3* represent tabu Comparison vs others Optimization Method.

Table 3. Comparison between optimization methods

Optimization Method	Advantages	Limitations
Genetic Algorithm (GA)	Strong global exploration	High computational cost
Particle Swarm Optimization (PSO)	Fast convergence	Can converge prematurely
Simulated Annealing (SA)	Escapes local optima	Slow convergence
Tabu Search (TS)	memory-guided search, suitable for discrete optimization	Requires tabu parameter tuning

4. EVALUATION METRICS

The proposed CS-TS-DNN model is extensively evaluated in terms of standard multi-class classification metrics (accuracy, precision, recall, and F1-score) and confusion matrix analysis. The metrics provide a reliable measurement of the model effectiveness on ECG arrhythmia classification, especially for imbalanced medical datasets such as INCART and MIT-BIH where minority heartbeat classes can be underrepresented. Overall classification correctness of all categories of heartbeat is Accuracy. However, since accuracy alone might provide a misleading view of the performance in the case of imbalanced datasets, precision and recall were also used to assess the quality of the class-specific predictions along with the F1 score.

$$Accuracy = \frac{TP+TN}{(TP+TN+FP+FN)} \tag{9}$$

$$Precision = \frac{TP}{(TP+FP)} \tag{10}$$

$$Recall = \frac{TP}{(TP+Fn)} \tag{11}$$

$$F1 - score = 2 * \frac{(Precision*Recall)}{(Precision+Recall)} \tag{12}$$

5. RESULTS AND DISCUSSION

5.1 Manual Control Point Selection of Cubic Spline Results

To have a baseline evaluation of the proposed model, we have explored some manually selected cubic spline control point configurations, with 10, 20, 34, 50 and 100 control points respectively for INCART. From the experimental results in *table 4*, it is observed that the selection of the spline length strongly affects the performance of ECG classification. For the manually selected configurations, the maximum accuracy of 98.27% was obtained by using 20 control points, followed by 50 and 100 control points with accuracies of 98.20% and 98.19% respectively on the validation set. Interestingly, the original ECG feature dimensionality of 34 points resulted in a lower validation accuracy of 97.72%. Hence, spline length matching to the original feature count does not guarantee optimal classification performance. These results indicate that ECG preprocessing parameters have a significant impact on the quality of the learned signal representation of the deep learning model. The training and validation accuracy is shown in *figure 3*, which exhibit a stable convergence behavior with little overfitting as they are very close to each other. Although longer spline lengths resulted in better preservation of the signal details, they did not improve the overall classification performance, likely due to higher sensitivity to noise and redundant variations in the signal. In addition, *figures 4 & 5* show confusion matrices that offer a detailed class-wise evaluation of the two best performed manual spline setups (10 and 20 control points).

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Table 4. Classification accuracy of manually cubic spline control point selection

Manual Cubic Spline Control Points Select	Accuracy
10	98.20%
20	98.27%
34	97.72%
50	98.19%
100	97.86%

Table 5. Classification report of highest manual cubic spline control point selected

Manual Cubic Spline Control Points Select	Accuracy	precision	recall	F1-score
10	98.20%	99.04%	98.20%	98.53%
20	98.27%	99.04%	98.27%	98.56%

A key parameter for ECG classification is the number of cubic spline control points. With 20 control points, the highest accuracy (98.27%) was achieved for manual splines, followed closely by 10 control points (98.20%) for automatic splines, as shown in *tables 4* and *5*. Increasing the number of control points above the optimal (e.g., 50 points and 100 points) did not improve classification, probably because excessively splines would preserve signal's redundant variations, as well as noise, which would be detrimental to the generalization ability. Moreover, both the 10 and 20 control point configurations showed high precision, recall and F1 score, all over 98%, proving the robustness of the proposed preprocessing framework, as shown in *table 4*.

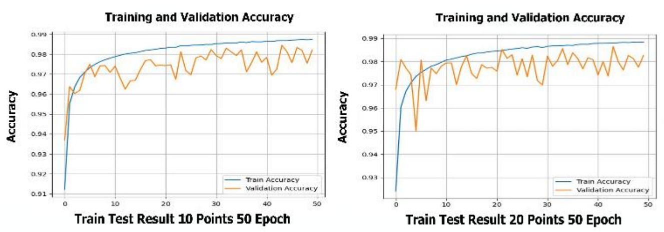

Figure 3. Training and validation accuracy curves

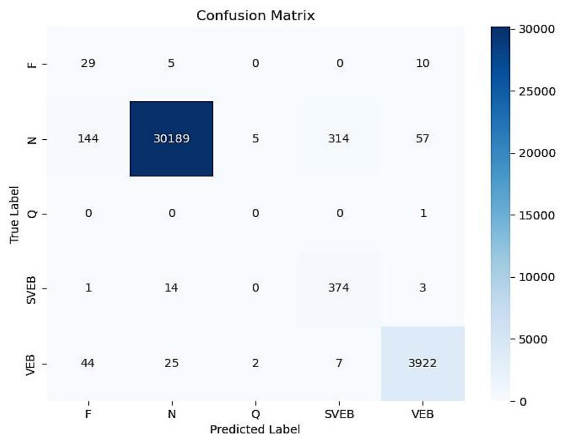

Figure 4. Confusion matrix of manual 10 cubic spline CPs

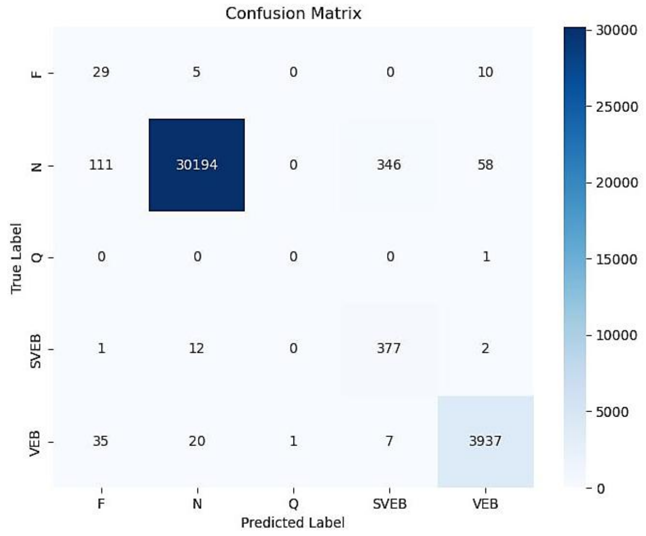

Figure 5. Confusion matrix of manual 20 cubic spline CPs

5.2. Optimization Tabu Search Control Point Selection of Cubic Spline Results

The proposed optimization model tested on both INCART and MIT-BIH to further evaluate the generalization. As with the baseline experiments, a 20 iteration TS optimization process was used to automatically determine the optimal cubic spline control point configuration. The results from the INCART dataset show the success of the TS algorithm in exploring the spline-length search space of [8,36]. When the initial spline length was set to L=34, which had a validation accuracy of 97.68%, the algorithm still found multiple improved configurations (e.g., 98.04% at L=32, 98.29% at L=30, 98.32% at L=23) to reach a maximum accuracy of 98.75% at L=19. outperforming all manually selected spline configurations. Subsequent evaluations of smaller spline lengths resulted in reduced performance, confirming that excessive smoothing negatively affects ECG morphology preservation and classification capability. To further validate our optimization model, we also initialized the optimization for MIT-BIH dataset using the original dimensional ECG features (L=187). The TS algorithm proceeded to update the Tabu List during optimization, while increasing validation accuracy from 97.68% to 97.75% (over 20 iterations), before converging to the optimal spline length of 162 control points. this indicates that the optimization model is able to successfully identified non-intuitive spline configurations that maximize validation accuracy, and could improve ECG representation quality on different datasets. The best validation accuracy is reported for each iteration of TS in *table 6* for INCART and *table 7* for MIT-BIH. *Figures 6* show the training-validation accuracy curves, and *figures 7* and *8* show the confusion matrix. *Figures 9* and *10* represent the Tabu Search convergence for each dataset. These results demonstrate that the addition of metaheuristic-driven preprocessing optimization to ECG classification may significantly improve performance over a more heuristic selection of splines by manual selection of CPs.

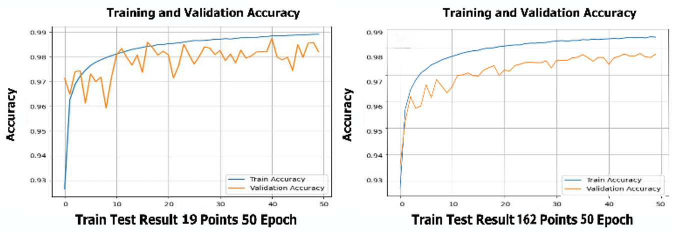

Figure 6. Training and validation accuracy curves

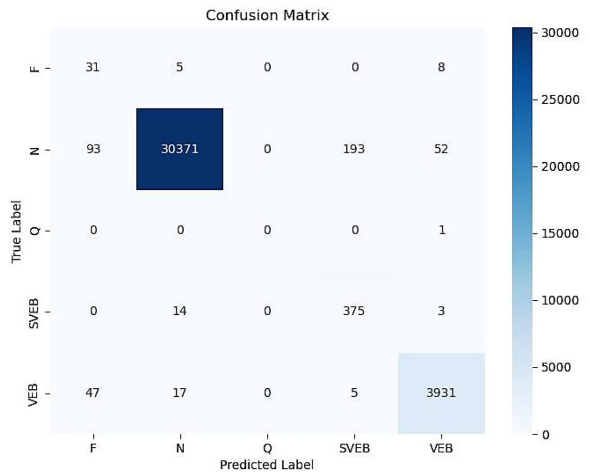

Figure 7. Confusion matrix of 19 CP for INCART

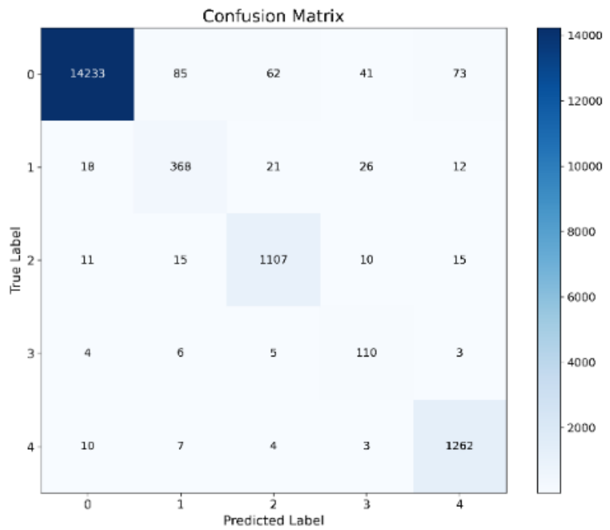

Figure 8. Confusion matrix of 162 CP for MIT-BIH

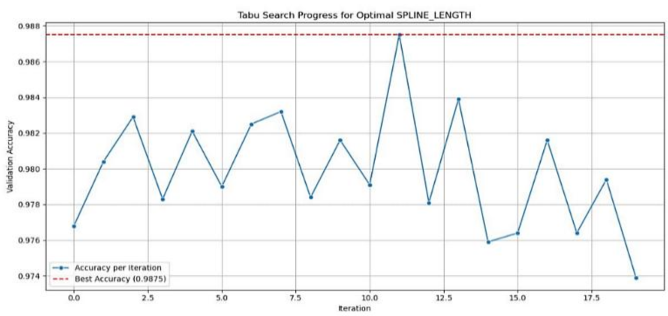

Figure 9. Tabu search progress for optimal Cubic Spline Control point selection for INCART

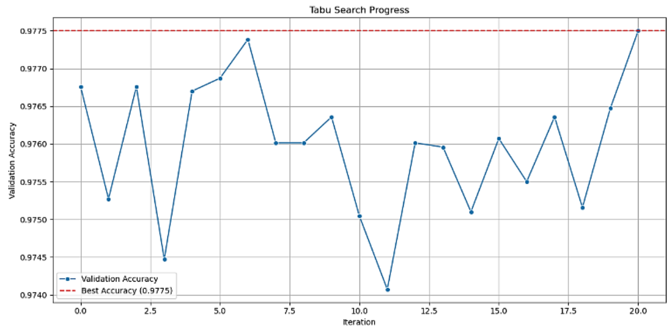

Figure 10. Tabu search progress for optimal Cubic Spline Control point selection for MIT-BIH

Table 6. Best Accuracy per Iteration of Tabu for INCART

Iteration	Best Validation Accuracy (Running Global Maximum)	Tabu list update
0 (Initial)	0.9768	[34]
1	0.9804	[34, 32]
2	0.9829	[34, 32, 30]
3	0.9829	[34, 32, 30, 28]
4	0.9829	[34, 32, 30, 28, 26]
5	0.9829	[32, 30, 28, 26, 25]
6	0.9829	[30, 28, 26, 25, 24]
7	0.9832	[28, 26, 25, 24, 23]
8	0.9832	[26, 25, 24, 23, 21]
9	0.9832	[25, 24, 23, 21, 22]
10	0.9832	[24, 23, 21, 22, 20]
11	0.9875	[23, 21, 22, 20, 19]
12	0.9875	[21, 22, 20, 19, 18]
13	0.9875	[22, 20, 19, 18, 17]
14	0.9875	[20, 19, 18, 17, 16]
15	0.9875	[19, 18, 17, 16, 14]
16	0.9875	[18, 17, 16, 14, 13]
17	0.9875	[17, 16, 14, 13, 11]
18	0.9875	[16, 14, 13, 11, 10]
19	0.9875	[14, 13, 11, 10, 12]
20	0.9875	Non-Tabu neighbors found. Stopping search.

Table 6 shows the results of this optimization process. With the initial spline length of 34, validation accuracy on the INCART dataset was 97.68%. In the first few iterations the performance quickly rose to 98.04% validation accuracy at a spline length of 32 and 98.29% at a spline length of 30, which demonstrates the effectiveness of this proposed Tabu Search optimization framework at finding the optimal cubic spline control point configuration. At the seventh iteration, the algorithm identified another improvement (Spline length: 23, Validation accuracy: 98.32%) and continued the search process, dynamically updating the Tabu List to avoid recently evaluated

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configurations. The global optimum was achieved at the 11th iteration (Spline length: 19, Validation accuracy: 98.75%). Results indicate that the Tabu Search strategy was able to find non-intuitive spline configurations that could significantly improve ECG classification. The results presented in *table 6* demonstrate the effectiveness of the proposed Tabu Search optimization framework for determining the optimal cubic spline control point configuration on the INCART dataset.

Table 7. Best Accuracy per Iteration of Tabu for MIT-BIH

Iteration	Best Validation Accuracy (Running Global Maximum)	Tabu list update
0 (Initial)	0.9768	[187]
1	0.9753	[187, 186]
2	0.9768	[187, 186, 185]
3	0.9745	[187, 186, 185, 183]
4	0.9767	[187, 186, 185, 183, 184]
5	0.9769	[186, 185, 183, 184, 182]
6	0.9774	[185, 183, 184, 182, 181]
7	0.9760	[183, 184, 182, 181, 180]
8	0.9760	[184, 182, 181, 180, 179]
9	0.9764	[182, 181, 180, 179, 178]
10	0.9750	[181, 180, 179, 178, 177]
11	0.9741	[180, 179, 178, 177, 175]
12	0.9760	[179, 178, 177, 175, 173]
13	0.9759	[178, 177, 175, 173, 172]
14	0.9751	[177, 175, 173, 172, 171]
15	0.9761	[175, 173, 172, 171, 169]
16	0.9755	[173, 172, 171, 169, 168]
17	0.9764	[172, 171, 169, 168, 167]
18	0.9752	[171, 169, 168, 167, 165]
19	0.9765	[169, 168, 167, 165, 163]
20	0.9775	[168, 167, 165, 163, 162]

As shown in the *table 8* above the search began with an initial spline length of 187 producing a validation accuracy of 97.68% and then iterating through any neighboring spline configurations as per the Tabu List (to prevent having examined that solution previously), with one or more of these neighboring configurations having experienced local decreases in their validation accuracy, while all iterations continued to be able to escape the local optima and improve the overall quality of their solutions. Validation accuracy for iteration 5 was 97.69% and for iteration 6 was 97.74%. At iteration 20, the highest validation accuracy was obtained (97.75%) from a spline length of 162, thereby substantiating that the Tabu Search Strategy produced highly efficient configurations arising from the Tabu Search Strategy were highly successful.

Table 8. Best manual cubic spline CPs selected vs. Best optimized cubic spline CPs selected using Tabu for INCART and MIT-BIH

Method	CPs	Accuracy	Precision	Recall	F1-score
Manually Cubic spline CPs selected	20	98.27%	99.04%	98.27%	98.56%
Optimized Cubic spline CPs selected using Tabu for INCART	19	98.75%	99.22%	98.75%	98.94%
Optimized Cubic spline CPs selected using Tabu for MIT-BIH	162	97.75%	97.73%	97.54%	97.60%

These result above shows that the spline control points directly affect how well we can preserve the morphology of ECG signals as well as the quality of downstream classifications. Traditional methods for preprocessing ECG signals use fixed interpolation parameters; however, our new model for classifying ECGs adaptively optimizes the control points of the spline based on how well we perform during validation testing. The best-fitting control points to use with our splines were found to be 19 in total for the INCART dataset and 162 in total for the MIT-BIH dataset, which is quite different than what would be expected from the original dimensions of the signals. This indicates that using heuristic methods to select optimization parameters may not result in "best natural" representations of ECG signals for classification by deep learning methods. Thus, this demonstrates the originality of combining metaheuristic optimization with spline-based preprocessing of ECG signals.

5.3. Computational Cost and Complexity Analysis

Retraining the deep neural network (DNN) for each candidate spline length in the proposed Tabu Search optimization framework contributes to a large part of its computational cost. For the MIT-BIH experiment, there were a total of 51 spline configurations that were considered, inclusive of the initial configuration as well as the admissible neighboring configurations over 20 iterations. The overall optimization time was approximately 18569.79 seconds or 309.50 minutes or 5.16 hours, with an average evaluation time of 364.11 seconds associated with evaluating each spline configuration. Even though the optimization process introduces additional computational costs within the offline phase of model development, this will be only performed once to establish the optimal spline configuration. After the optimization of the spline configurations, the final CS-TS-DNN runs independently of any Tabu Search overhead for the purposes of inference. As shown in *table 9*, the deployed CS-TS-DNN model contains less than 0.256 million parameters, has an estimated size of under 0.98 MB, and has an inference time of approximately 1.8 ms per ECG sample. Therefore, the proposed model provides improved preprocessing optimization while allowing for an efficient real time deployment capability.

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Table 9. The computational efficiency of proposed model

Model	Parameters (Millions)	Model Size (MB)	Inference Time per Sample (ms)	Hardware
Proposed CS-DNN with INCART	~0.183M	~0.70 MB	~1.3 ms	CPU: Ryzen 7 5800H, RAM: 16.0 GB, Graphic Card: RTX 3060
Proposed CS-DNN with MIT-BIH	~0.256M	~0.98 MB	~1.8 ms	CPU: Ryzen 7 5800H, RAM: 16.0 GB, Graphic Card: RTX 3060

6. COMPARISON *Vs* OHER STUDIES

The author in [21] achieved 97.23% accuracy using a lightweight CNN on raw ECG signals without adaptive resampling. Another author in [22] reported 94.17% accuracy with a multimodal augmentation network but relied on fixed signal-to-image conversion without optimizing signal representation. While [23] attained 96.60% using Jaya-optimized wavelet features, but their method is computationally heavy. The author in [24] reached 97.57% with EEMD and SVM but lacked deep learning expressiveness. Another author in [25] scored 98.37% using PMAT-based 2D-CNNs, yet used non-adaptive, high-dimensional transforms. Collectively, these works highlight a consistent gap: none optimize the fundamental signal interpolation or resampling hyperparameters in a data-driven, metaheuristic manner, leaving room for performance gains through intelligent preprocessing precisely the contribution of our Tabu Search–optimized cubic spline framework.

In contrast, our proposed CS-TS-DNN model fundamentally rethinks preprocessing as an optimizable component of the learning pipeline. By integrating cubic spline interpolation with Tabu Search metaheuristic optimization, we enable data-driven discovery of the optimal control point count of cubic spline = 19 that maximizes validation accuracy (98.75%) for INCART dataset and 162 that maximizes validation accuracy (97.75%) for MIT-BIH. This result is not only superior to all prior works as shown in *table 10* but also validates and refines our initial heuristic, our manual selection of 20 control points (98.27% accuracy) was already near-optimal, and the Tabu Search further optimized the configuration to the true global optimum. More to the point, our approach directly correlates the quality of preprocessing to the classification performance, such that morphological features that are especially important to rare arrhythmias are not distorted through the manipulations of the user. This metaheuristic optimization synergy signifies a more systematic and adaptive preprocessing strategy between the ad hoc based design to performance conscious, automated preprocessing and thus establish a new standard of robustness and reproducibility in the ECG deep learning systems.

Table 10. Comparison with SOA studies

Author(s)	Method	Application	Accuracy
Farag 2023 [21]	Matched Filter + Tiny CNN	Inter-patient arrhythmia classification (validated on INCART)	97.23%
Xu et al. 2024 [22]	Multimodality Data Augmentation Network (MM-DANet)	Arrhythmia classification on INCART	94.17%
Ramasamy et al. 2023 [23]	Enhanced Jaya-Optimized TQWT + Stacked Ensemble SVM	INCART arrhythmia classification	96.60%
Rajesh & Dhuli. 2017 [24]	EEMD + SMO-SVM	Five-class heartbeat classification on INCART	97.57%
Mokhtari et al. 2025 [25]	PMAT + 2D-CNN	INCART arrhythmia classification	98.37%
Our Model	**CS-TS-DNN**	**INCART MIT-BIH**	**98.75% 97.75%**

7. CONCLUSION

In this study, a novel model CS-TS-DNN was proposed to classification of ECG arrhythmia. CS-TS-DNN combines a Cubic Spline Interpolation with a Tabu Search Optimization method for adaptive preprocessing of ECG signals and subsequent deep learning-based arrhythmia classification. In contrast to standard techniques based on manual parameter selection, our model finds automatically the optimal spline configuration using a metaheuristic algorithm, which is driven by the performance on validation data. The proposed model was experimentally evaluated using two public ECG datasets - INCART and MIT-BIH Arrhythmia dataset. It was shown that the application of the proposed optimization framework significantly boosts classification performance. Specifically, we were able to achieve a validation accuracy of 98.75% on INCART with optimized spline length of 19, beating all manually selected configurations. Further cross-validation experiments on MIT-BIH Arrhythmia dataset achieved an accuracy of 97.75% with optimized spline length of 162. Thus, it can be concluded that the suggested optimization methodology is robust and can be effectively used for processing ECG signals. Our results prove that optimization of preprocessing is a crucial step towards successful deep learning-based ECG signal processing. At the same time, the proposed model remains computationally efficient with lightweight architecture, low memory requirements and inferencing time respectively. Further work will focus on using of additional metaheuristic algorithms, larger multi-lead ECG datasets, and transformers-based neural networks.

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