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PSO-Pelican Arrhythmia Optimize: Revolutionizing Arrhythmia Detection via Automated Deep Learning Parameter Tuning

Jayanthi[1*], Prasanna Devi[1], Mohammed Zakariah[2], Abdulaziz S. Almazyad[3]

[1] Department of Computer Science and Engineering, SRM Institute of Science and Technology-Vadapalani Campus, Chennai 600026, India
[2] Department of Computer Sciences and Engineering, College of Applied Science, King Saud University, Riyadh 11543, Saudi Arabia
[3] Department of Computer Engineering, College of Computer and Information Sciences, King Saud University, Riyadh 11543, Saudi Arabia

Corresponding Author Email: js8683@srmist.edu.in

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ABSTRACT

Automatic hyperparameter optimization is crucial for reliable cardiac arrhythmia classification using electrocardiograms (ECGs). However, existing approaches often struggle to identify intricate arrhythmia patterns, leaving a significant research void. In this study, we introduce the first deep PSO-POA framework, integrating Particle Swarm Optimization (PSO) and pelican optimization methods, to address this challenge. Our framework enhances Deep Neural Network (DNN) designs for ECG arrhythmia pattern detection by providing a solid basis that includes chaotic initialization, a calibrated objective function for model assessment, and a balanced approach between exploration and exploitation tactics. We automate systematic and data-driven hyperparameter adjustment in the unique AutorythmAI system. Leveraging a diversified ECG database with numerous arrhythmia patterns for validation, we optimize hyperparameter configurations for multi-class DNN models through careful testing and validation processes. Model performance is rigorously evaluated using cross-validation, sensitivity analysis, and benchmark comparisons. With different parameter choices, the ResIncept and VGGRes models demonstrate impressive accuracies of 96.40% and 97.39%, respectively. To enhance adoption and reproducibility, we meticulously document the framework's implementation details, dataset sources, and hyperparameter configurations, making them publicly available for future studies to replicate and benchmark against. Our unique system eliminates manual hyperparameter selection, thereby improving arrhythmia detection accuracy, openness, repeatability, and field adoption. Also, we have compared data from different countries to prove that the model is globally working well without any bias.

1. INTRODUCTION

Cardiovascular illnesses persist as a substantial worldwide health challenge, with arrhythmias emerging as a key issue [1]. Prompt and precise arrhythmias identification is essential for efficient medical management and enhanced patient results [2-4]. Automated machine learning algorithms have demonstrated significant potential in improving the efficiency of arrhythmia detection in recent years. Nevertheless, there is still a significant deficiency in optimizing these systems to attain comprehensive multi-class detection capabilities [5, 6]. This study aims to address this deficiency by integrating the PSO and the Pelican Arrhythmia Optimize (PAO) framework in a novel manner. Collectively, they are referred to as PSO-Pelican Arrhythmia Optimize, and their objective is to revolutionize the detection of arrhythmias by utilizing automated deep learning parameter optimization [7-9].

Furthermore, arrhythmia classification predominantly depends on deep learning approaches, which utilize their ability to evaluate complex electrocardiogram (ECG) patterns with exceptional accuracy [10-12]. Neural networks, specifically deep learning models, have exhibited exceptional proficiency in identifying intricate patterns present in ECG signals. Nevertheless, the efficiency of these models is closely linked to the accurate adjustment of hyperparameters, which continues to be a significant obstacle in the field of arrhythmia detection [13-15]. Although there are advanced deep model architectures specifically developed for arrhythmia detection, their performance generally fails to meet expectations due to insufficient optimization techniques [16, 17]. The limitations become particularly evident in cases requiring multi-class identification, since existing algorithms struggle to distinguish between distinct ECG patterns indicative of various arrhythmic disorders [18, 19].

Further, the complexities related to hyperparameter adjustment in arrhythmia detection are manifold. Primarily, the extensive and intricate range of parameters in deep learning models renders manual adjustment impracticable and time-consuming. Automated methods, such as grid and random search, have been used to explore this domain [20-22]. However, they often lack the efficiency required to successfully negotiate the complexities of hyperparameter landscapes [23, 24]. As a result, this restriction impedes the ability to fully exploit deep learning models' capabilities in accurately distinguishing small distinctions across different arrhythmia categories.

Moreover, given these difficulties, combining PSO with the Pelican Arrhythmia Optimize framework presents itself as a new and promising approach to tackle the complexities of hyperparameter tuning [25-28]. The PSO algorithm offers a powerful method for efficiently exploring the extensive parameter space of deep learning models by leveraging insights from collective behavior seen in swarms. The Pelican Arrhythmia Optimize framework is a specialized platform for assessing and refining deep learning models that utilize ECG data, specifically focusing on arrhythmia detection [29-32].

Likewise, the combination of PSO with Pelican Arrhythmia Optimize significantly changes the optimization of deep learning models for detecting arrhythmia [33-35]. PSO utilizes the combined intelligence of particle swarms to effectively explore the hyperparameter environment, continuously adjusting and refining the model configuration to reach exceptional performance [36-38]. Whereas, this work aims to demonstrate that PSO-Pelican Arrhythmia Optimize may enhance the accuracy and efficiency of automated deep learning parameter optimization for detecting arrhythmia [39, 40].

Detecting arrhythmia with complex deep learning models requires adaptive optimization for multi-class settings [41, 42]. Despite their complexity, these models lack thorough optimization methods. This results in suboptimal parameter settings and limited arrhythmic pattern application [43-45]. This also limits real-time change, which is essential for medicinal interventions [46, 47]. This study proposes advanced optimization methods for detecting numerous types of arrhythmia to overcome present constraints. The suggested strategy, called PSO-PAO optimization, aims to improve the discriminative ability of deep learning models in discriminating between different arrhythmic circumstances while increasing accuracy, sensitivity, and specificity [48]. This strategic improvement is expected to substantially contribute to the complex challenge of categorizing arrhythmias. The work rigorously evaluates the effectiveness of the PSO-PAO-optimized deep learning model using a large dataset that includes various types of arrhythmic scenarios with many classes. The primary objective is to create an automated, reliable arrhythmia classification system. This will be achieved by carefully changing neural network hyperparameters via PSO-PAO optimization. To improve clinical reliability and precision, this research will develop automated arrhythmia detection systems.

Figure 1 shows the cutting-edge PSO-Pelican Arrhythmia Optimizations framework, which automatically optimizes deep learning parameters to detect arrhythmias. Multi-modal ECG data, including visuals for analysis, is pre-processed first. The second phase uses complex feature engineering, including feature selection and extraction, to improve the dataset's distinctiveness. AutorythmAI, a complex system that automates model selection and hyper-parameter tuning, is introduced in the third phase. This optimizes model performance without operator intervention, making the process more efficient. For reliable arrhythmia detection, the selected model receives the augmented and polished images. The PSO-Pelican Arrhythmia Optimizations system improves arrhythmia diagnosis by merging data pretreatment, feature engineering, and automated deep learning optimization.

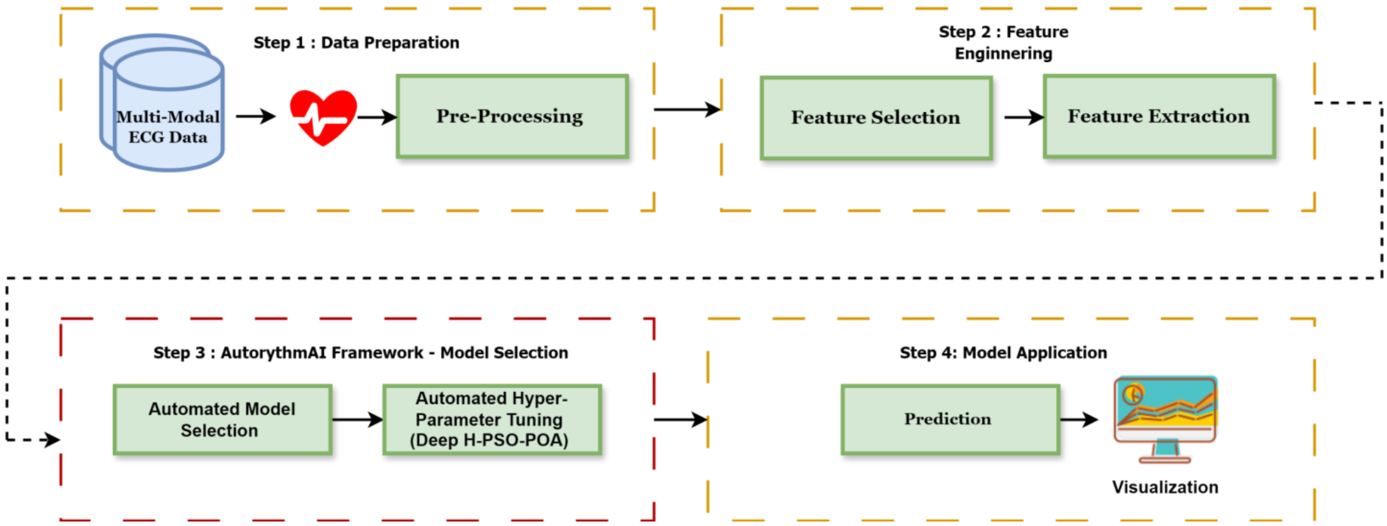

Figure 1. Framework for PSO-Pelican arrhythmia optimization detection via automated deep learning parameter tuning

The major contributions to this paper include:

(1). Innovative Hyperparameter Tuning: Introducing a novel two-phase algorithm combining PSO and POA to automate hyperparameter tuning in deep learning models for enhanced accuracy of arrhythmia detection.

(2). Enhanced Arrhythmia Detection: Showing better accuracy and robustness in identifying different arrhythmic patterns through optimized deep learning models helps doctors make more accurate diagnoses.

(3). Framework for Healthcare Automation: Providing a versatile framework applicable in healthcare settings, this algorithm facilitates automation in developing reliable arrhythmia detection systems.

(4). Adaptive Model Refinement: Implementing an adaptive mechanism for continual model improvement, ensuring sustained accuracy in dynamic healthcare scenarios.

(5). Interpretable Decision Framework: Establishing methods for clearer interpretation of model decisions and enhancing transparency and understanding for clinicians implementing the system.

The structure of the paper proceeds as follows: Section II delves into related work pertaining to the addressed issue, providing comprehensive insights into prior research. Section III presents preliminary information, laying the groundwork for the subsequent discussions. Section IV entails a comprehensive overview of the proposed deep H-PSO-POA algorithm. The experimental findings and discussions are outlined in Section V, while Section VI encapsulates the conclusion of this research.

2. RELATED WORK

The emerging discipline of deep learning has brought about a significant transformation in multiple sectors, particularly in healthcare, where it has demonstrated great promise in enhancing the precision and effectiveness of diagnostic procedures. Developing deep learning models has greatly advanced the identification of arrhythmia, a crucial component of monitoring cardiovascular health. Yet, the maximum efficiency of these models relies on successfully adjusting hyperparameters, which is a complicated and demanding endeavor. According to the study [49], obtaining the most optimal model configurations necessitates a comprehensive comprehension of machine learning algorithms and expertise in optimization approaches. Furthermore, the impact of the tuning technique on the sensitivity of optimizer comparisons continues to be a significant concern, even with the progress made in hyperparameter tuning methods [50].

In general, hyperparameter tuning in deep learning models presents significant challenges due to the high dimensionality of the search space and the intricate interactions between hyperparameters. The selection of optimal hyperparameters directly impacts the model's performance, convergence speed, and generalization ability. However, manual tuning of hyperparameters is time-consuming, labor-intensive, and often leads to suboptimal results.

However, the high cost of computation and machine learning proficiency prevent wider adoption. Genetic algorithms, PSO, POA, and simulated annealing navigate complex parameter spaces efficiently [51]. These solutions are flexible and can overcome past limits. Because ECG signal processing is so complex, arrhythmia detection research requires specialized optimization approaches [52]. The performance metrics and restrictions of deep learning models used to detect arrhythmia have also been extensively studied. It is becoming clear that these models require significant computational resources and customized optimization strategies to maximize their use [53]. This review consolidates and evaluates existing knowledge on hyperparameter tuning strategies and their role in improving deep learning models' arrhythmia detection [54].

He et al. [55] created a system for identifying cardiac arrhythmia using Internet of Things electrocardiograms (ECGs). The study emphasizes the need for advanced diagnostic methods to reduce cardiac arrhythmia health risks. The authors use the well-known MIT-BIH-AR dataset and present a unique method that combines dynamic ensemble selection (DHCAF) with multi-channel convolutions (MCHCNN) to detect arrhythmias in IoT-based ECGs Improved diagnostic accuracy is possible with feature engineering and deep learning. However, the paper acknowledges the framework's lack of automatic hyperparameter change, suggesting a future improvement. The results demonstrate the framework's importance in enhancing IoT-based ECG arrhythmia detection. Furthermore, it stresses the need to resolve recognized limits for further study and optimization.

The authors [56] also addressed the crucial issue of identifying arrhythmias using ECG signals. For this purpose, the article recommends employing an advanced deep convolutional neural network (D-CNN). Their method also uses continuous wavelet transform and coefficient of fractional (CoF) features. The beginning stresses the importance of accurate arrhythmia diagnosis for quick treatment. Current techniques are lacking; hence the issue statement emphasizes automated hyperparameter optimization and reduced computing resource needs. The paper tests the proposed approach using the widely used MIT-BIH-AR dataset. Systematic D-CNN and CoF feature integration is novel. However, the lack of automated hyperparameter change poses model optimization concerns. The study classifies 2D ECG signals with 95.84% accuracy, proving the approach works. However, the model's high computational requirements emphasize the need for future studies to improve resource efficiency. Atal and Singh's research is significant. However, more optimization research is needed to improve its practicality.

Bouaziz et al. [57] also addressed the crucial issue of automatically categorizing ECG arrhythmias. Their approach uses an MLP neural network and a novel PSO metaheuristic. Due to rising cardiovascular disease rates, accurate ECG arrhythmia categorization is crucial. Current methods are vulnerable to local optima and computationally intensive, according to the authors. They propose integrating MLP and PSO to overcome these limits, taking advantage of each method's capabilities. The five-category MIT-BIH Arrhythmia Database was used for evaluation. PSO is used to train the Multilayer Perceptron (MLP) for better categorization. The methodology's 94.44% accuracy rate shows its efficiency. This research provides a reliable ECG arrhythmia classification method. It also shows how neural network topologies and unique metaheuristics can improve medical diagnosis accuracy and efficiency.

In addition, Nainwal et al. [58] also identify ECG data using a DNN classifier and a modified Pigeon-Inspired Optimizer dubbed (MPIO). This research aims to overcome wider application restrictions and present methodology computational requirements. The issue statement requires a clear and effective ECG categorization system. The authors tested their approach on an ECG dataset and achieved 95.01% accuracy. This investigation shows that the recommended methodology is practical in real life. The innovative method uses DNN and Multiple Input and Output (MPIO) approaches to improve categorization. The study found that the proposed strategy improves classification accuracy, advancing ECG signal processing. The results of this study resolve constraints and allow this approach to be used in clinical settings and other fields that require precise ECG signal classification.

Over the past several years, there has been significant interest in combining computational intelligence and medical diagnosis. This has led researchers to investigate new methods to improve the accuracy of classifying complicated health situations. Baños et al. [59] introduced a novel hybrid model combining PSO and CNN for cardiac arrhythmia classification, addressing the underutilization of PSO-CNN-SVM hybrids in prior studies. Their tests on chronic renal illness datasets achieved an impressive 89.01% accuracy, underscoring the importance of diverse and accurate datasets for validating machine learning models. This research utilizes a methodology that incorporates PSO to optimize the parameters of Convolutional Neural Networks (CNNs) [60]. This approach sets it apart from other studies, making it distinctive. Based on the findings, the suggested hybrid model demonstrates effective performance and has the potential to classify cardiac arrhythmias accurately and consistently. This would contribute to our overall understanding in the realm of medical diagnostics.

Moreover, Tuerxun et al. [61] improved wind turbine fault classification with Broad Learning system (BLS)and Enhanced Pelican optimization. Real-time monitoring and data collecting in renewable energy generation require accurate fault categorization, which their IoT-integrated methodology overcomes. The work emphasizes the need for an effective optimization approach to manage premature convergence and large dimensionality. Key issues are addressed by the Enhanced POA. It outperforms previous algorithms in wind turbine fault categorization, suggesting it could improve turbine operations and maintenance.

Table 1 shows the list of past references, including methodology used, dataset, results, and limitations.

Whereas, Table 2 demonstrates significant deficiencies in studies about the classification of cardiac arrhythmia. This demonstrates the pressing necessity for deep learning models specifically tailored to the intricate responsibilities of detecting arrhythmias. Recognizing these gaps highlights the necessity of progressing approaches beyond traditional frameworks. Using metaheuristic algorithms in healthcare can lead to hybrid models, improving classification accuracy. Tailoring PSO to address convergence issues, especially local optima, presents opportunities to enhance the reliability of cardiac arrhythmia classification methods.

In healthcare, particularly in the vital area of diagnosing arrhythmia using ECG data, various challenges have highlighted the need for concentrated advancement. The gaps clearly suggest the need to improve models, find new methodologies, and change optimization strategies. The goal is to improve their practicality and effectiveness in complex healthcare by properly diagnosing arrhythmias using ECG data. Due to the shortcomings found in this specialized field, algorithmic precision and optimization must be accelerated. A detailed optimization plan with many strategies is needed. Strategic convergence integrates two optimization methods into a single framework to optimize parameters synergistically. This hybrid approach enhances capacities and deepens solution exploration. It offers better parameter adjustment and model accuracy. Healthcare models must incorporate optimization approaches to tackle real-world ECG arrhythmia detection complexity.

To summarize, the proposed shift towards combining optimization techniques in a cohesive framework has great potential. This novel method is ready to revolutionize the field of parameter tuning in healthcare, leading to greater effectiveness of models and, as a result, increased accuracy in detecting arrhythmias using ECG signals.

Table 1. Arrhythmia detection frameworks: Methodologies and limitations

Paper Cited	Approach/Methodology	Dataset Used	Accuracy	Limitations
[55]	DHCAF (Dynamic Ensemble Selection), MCHCNN (Multi-channel Convolutions)	MIT-BIH-AR	Accurate arrhythmia detection in IoT-based ECGs, combining feature engineering and deep learning	Lack of automated hyperparameter tuning for the framework
[56]	Continuous Wavelet Transform, D-CNN, CoF	MIT-BIH-AR	95.84% accuracy in 2D ECG signal classification	No automated hyperparameter tuning, computational resource requirement
[57]	MLP (Multi-Layer Perceptron)+PSO	MIT-5 Classes	Achieving 94.44% accuracy	Susceptibility to local optima, computational intensity
[58]	MPIO (Multi-Population Input Optimization)+DNN	ECG dataset	Accuracy of 95.01%	Lack of broader application, computational demands
[59]	PSO-CNN (Convolutional Neural Network)-SVM (Support Vector Machine)	Chronic Kidney Disease	Accuracy of 89.01%	Few studies utilizing this approach
[61]	Grey Wolf Optimization, Genetic Algorithm	IoT Framework	Enhanced accuracy for IoT	Challenges with premature convergence, handling high dimensionality

Table 2. ECG and optimization: Identified research gaps

Research Domain & Papers Cited	Research Gap	Explanation of Identified Gap
Deep Learning Applications for ECG [38-40]	Lack of deep model integration for CAs classification	The lack of strong deep models for cardiac arrhythmia classification limits pattern identification, but transfer learning may help.
Optimization Techniques [41, 42]	Limited use of MA in healthcare applications	Metaheuristic Algorithms (MA) that optimize neural network performance have been understudied in healthcare and might enhance hybrid model categorization.
Convergence Challenges [43, 44]	PSO's susceptibility to local optima	PSO shows rapid convergence to local optima, limiting exploration of diverse solution spaces; addressing this limitation requires modified PSO versions.

3. FUNDAMENTAL CONCEPTS

3.1 ECG data collection

A multi-modal ECG dataset combines ECG data with additional signals like respiratory or blood pressure data. This integration of diverse signals offers supplementary insights, enhancing ECG analysis accuracy for detecting arrhythmias, identifying cardiac issues, and monitoring vital signs in medical procedures. These datasets, such as CPSC2018 [62], St. Petersburg INCART [63], CinC2020, Georgia [64], and CACHET-CADB [65], are publicly accessible, enabling researchers to benchmark their algorithms and collaborate within the field. The data formats vary between header files (.hea) detailing 12 lead signal values and diagnostic information, and mat files (.mat) containing patient ECG signals. Table 3 gives the summary of the multimodal ECG data used. For testing the data, the Chapman-Shaoxing 12-lead ECG Database [66] would be utilized. This database comprises 45,152 ECGs extracted from 34,905 10-second recordings, all of which are sampled at a frequency of 500 Hz. This dataset provides a substantial volume of ECG data, allowing for comprehensive testing and validation of the proposed arrhythmia detection framework. The PTB-XL [67] dataset comprises over 21,000 12-lead ECG recordings from 1,525 patients, encompassing a wide spectrum of cardiac conditions and arrhythmias used as benchmark dataset for comparison. Similarly, the Georgia ECG dataset offers ECG recordings collected from patients in the Georgia region, providing additional data for research and validation purposes used for benchmark data and comparison.

In conclusion, our study leveraged diverse datasets from different countries to demonstrate the global applicability and robustness of our model for cardiac arrhythmia detection. By utilizing datasets such as the Chapman-Shaoxing 12-lead ECG Database, PTB-XL dataset, and the Georgia ECG dataset, which represent varied demographics and populations, we ensured that our model's performance was evaluated across a wide spectrum of cardiac conditions and patient profiles.

Table 3. Summarization of multimodal ECG database

Dataset Name	Number of Subjects	Female (F)	Male (M)	ECG Signal Length
CPSC2018	6877	3178	3699	6s-60s
St. Petersburg INCART	32	15	17	1800s
Georgia	10,344	4793	5551	10s
CACHET-CADB	24	9	15	10s

3.2 Multimodal dataset collaboration and data balancing

This section merges datasets while preserving data properties. Empty data, label, filename, gender, and age lists are initialized. We load each dataset separately and add its data and information to their lists. Concatenating these lists into NumPy arrays ensures order. The combined dataset keeps all data and labels. We extracted 3,252 abnormal and 2,568 standard signals from each dataset, ensuring a balanced class distribution without additional data-balancing.

3.3 Custom AutoRhythmAI model for ECG arrhythmias

Automatic Machine Learning (AutoML) strengthens AI standardization. It makes machine learning accessible with a button press or hides algorithm execution, data pipelines, and code [68]. This expertise is promising for research. AutoML is a dynamic system with great potential despite being built for task automation. Our ECG arrhythmia detection model cannot be customised using AutoML. Customized AutoRhythmAI algorithms for ECG arrhythmia identification in diverse datasets are our solution. Integrating hybrid model automation is stressed.

The AutoRhythmAI Model's meticulous approach to detecting arrhythmias in ECG data is depicted in Figure 2, visually outlining the sequential procedures involved in our groundbreaking model. The system illustrates the complex steps in data processing, encompassing preprocessing, model training, and validation, showcasing the proposed system's comprehensive nature. Our system has many strengths, but automated hyperparameter optimization is lacking. Model performance and generalization depend on this automated modification. Without it, the framework may struggle to attain optimal configurations and accuracy. Automatic hyperparameter adjustment should be prioritized for model resilience and efficacy in future editions.

3.4 PSO

PSO is a metaheuristic method devised to discover global maxima or minima within potential solution spaces. Inspired by the collective movement behaviors seen in flocks of birds or schools of fish, PSO's operation combines individual decisions with collective behaviors. Initially proposed by Trojovský and Dehghani [69], PSO has seen various modifications while retaining its fundamental operators. The algorithm calculates new particle positions by determining velocities influenced by the best global and current particle positions. The velocity update formula is defined as:

3.4.1 Velocity update

$$v_{i_{t+1}} = w * v_{i_t} + c1 * r1 * (p_{best_i} - p_{i_t}) + c2 * r2 * (p_{gbest_i}) - p_{i_t} \tag{1}$$

- $v_{i_{t+1}}$: Particle velocity at time t+1, v_{i_t}-Particle velocity at time t.
- *w*: Coefficient of inertia, adjusting with particle speed.
- *c1*, *c2*: Cognitive and social coefficients.
- *r1*, *r2*: Vectors of random values between 0 and 1, matching the length of the velocity vector.
- p_{best_i}: Best position attained by particle i, p_{i_t}Position of particle i at time t.
- p_{gbest_i}: Best overall position of the entire swarm.

Once velocities are updated, particle positions in iteration t+1 are calculated.

3.4.2 Position update

$$p_{i_{t+1}} = p_{i_t} + v_{i_{t+1}} \tag{2}$$

- $p_{i_{t+1}}$: New position of particle i in iteration t+1.
- p_{i_t}: Previous position of particle i calculated in iteration t.
- $v_{i_{t+1}}$: Velocity vector obtained using the velocity update formula.

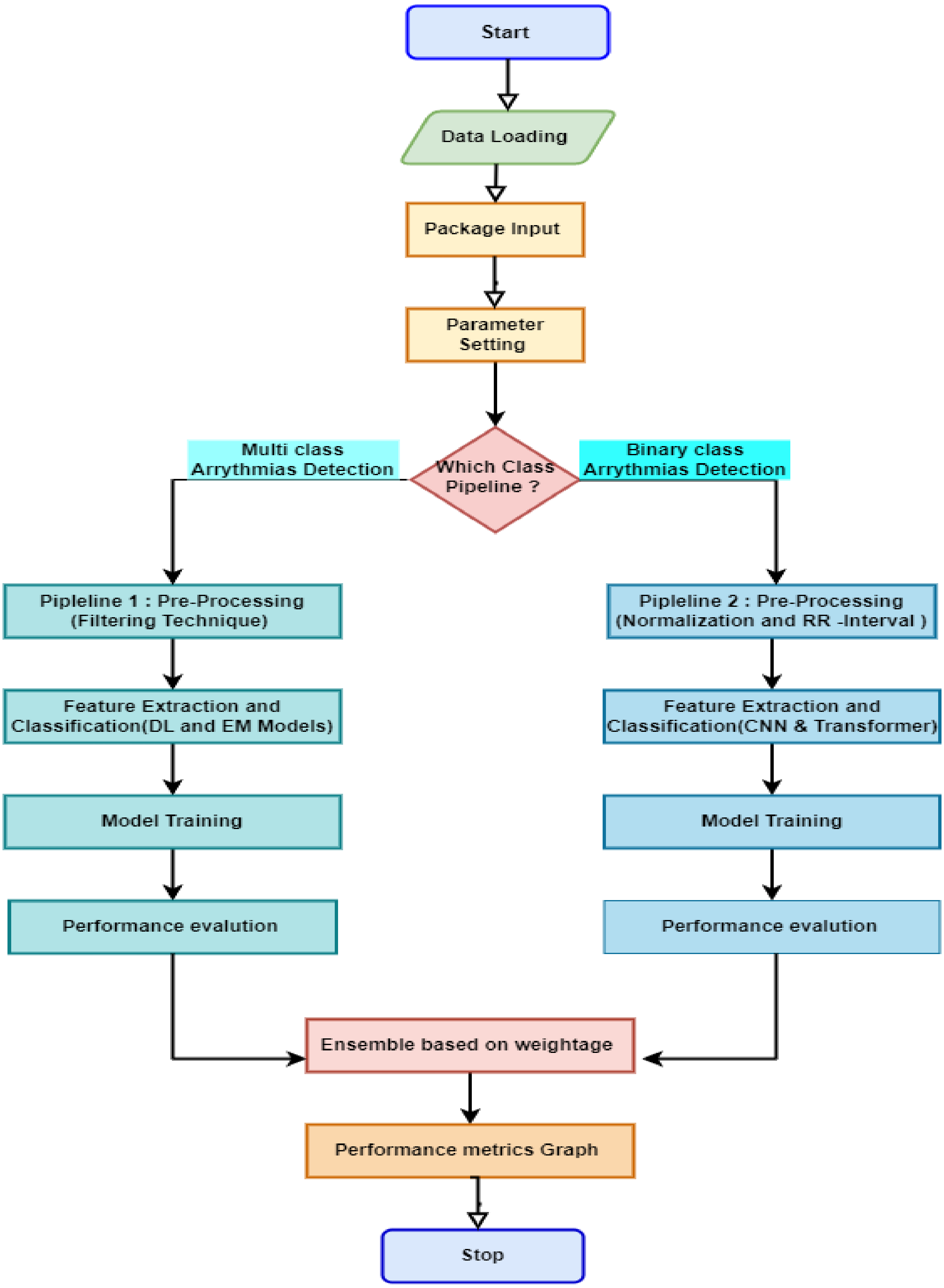

Figure 2. AutoRhythmAI model: ECG arrhythmia detection workflow

3.5 POA

The POA draws inspiration from the cooperative foraging behavior observed in pelican birds, presenting itself as a nature-inspired metaheuristic algorithm for optimization tasks. Here's a structured breakdown of the Key concepts of POA algorithm:

Exploration: Involves exploring new positions in the search space to discover potentially better solutions.

$$New_{Pos} = X(i,j) + rand(1,1) * (Agents\_Target - I * X(i,j)) \tag{3}$$

Exploitation: Utilizes discovered positions to exploit and fine-tune optimization solutions.

$$New_{Pos} = X(i,j) + 0.2 * \left(1 - \frac{t}{T}\right) * (2 * rand(1,1) - 1) * X(i,j) \tag{4}$$

The algorithm iteratively generates prey positions, updates positions for exploration and exploitation across dimensions, and outputs the best candidate solution obtained through the POA.

4. ARRYTHMIAS DETECTION USING THE DEEP PSO-POA CLASSIFIER

This section details arrhythmia categorization via the customized AutorythmAI framework, boosted by the Deep PSO-POA Classifier. Heart data in ECG form undergoes collection, preprocessing, and is then used in AutorythmAI's DNN models, optimized by PSO-POA. Leveraging PSO-POA, the DNN efficiently extracts features, enabling autonomous arrhythmia classification. The validation methodology for the deep PSO-POA framework for cardiac arrhythmia classification using ECGs would typically involve several steps to ensure the robustness and reliability of the developed models. Here's a suggested validation methodology:

4.1 Pre-processing techniques for multi-class distribution

First, ECG data are pre-processed to detect arrhythmia. Our approach to multi-class pre-processing a dataset with 27 distribution classes focused on signal length standardization and data labelling. Machine learning techniques like one-hot encoding and Multilabel binarize enhance it. Data processing was efficient and effective using these procedures, meeting model requirements.

4.2 Proposed deep PSO-POA optimization for arrhythmia classification (model training)

Deep NN classifiers on Multi class distribution are highly esteemed for their proficiency in parameter reduction while upholding data quality, ensuring optimal convergence speed in comparison to other classifiers. Within our proposed model, disease classification is executed through the application of a Deep PSO -POA based DNN classifier. This model operates by optimizing parameters directly from the provided data. The DNN architecture adeptly extracts confined features from input data, significantly enhancing classification performance. The classifier is trained effectively using PSO-PAO optimization, enabling efficient learning from input data and improved classification performance.

4.2.1 Chaos Initialize population

In PSO-POA optimization, initial positioning of people is usually randomized, which may cause an uneven population distribution and reduced solution accuracy. Chaos theory-based sequences are random and bounded. Logistic Map erratic mapping generates a more uniformly dispersed and investigated chaotic sequence. Population variety increases greatly, enhancing the algorithm's performance. This study provides Logistic chaotic mapping to improve PSO-POA optimization initialization by improving navigability. This update allows a more homogeneous population in the flamingo optimization search space during initialization. After chaotic sequence generation, this chaotic space is mapped onto the optimization problem's solution space, following the optimization variables. The mapping process follows.

The steps to initialize the population using chaos are:

1) Generate initial PSO-POA individual Y as a random d-dimensional vector within $[-1, 1]$.
2) For the remaining $N-1$ individual: Utilize the logistic map equation x_{n+1}=r*x_n*(1-x_n) for each dimension of Y, ensuring values are in the -1≤x_n≤1 range.
3) Map the obtained chaotic sequence into the search space:

Equation: *xid = Ld+(1+xid)×(Ud-Ld)/2*

xid denotes the position of the ith individual in the d-dimensional search space.

Ud and Ld represent the upper and lower bounds, respectively, of the search space.

xid is derived from the logistic chaotic sequence as the coordinate of the ith individual.

4.2.2 Objective function

The objective function trains and evaluates a multi-class DNN model for ECG arrhythmia identification. It decodes hyperparameters from a position, builds and compiles a DNN model, trains it on training data, and evaluates its performance using test accuracy. Hyperparameters are decoded from a specific position to build a DNN model for ECG arrhythmia detection via the objective function. It includes these steps:

(1). The decoding process extracts learning rate, batch size, and hidden units from the provided position.

(2). Model Construction: Creates a DNN model using Conv1D layers, Batch Normalisation, Global Average Pooling, and Dense layers using hyperparameters.

(3). DNN Model Compilation: Utilizes Adam optimizer and categorical cross-entropy loss.

(4). Model Training: Apply hyperparameters and settings to train the model on training data.

(5). Evaluation: Determines model accuracy tested on validation dataset.

(6). Returns: Optimize performance metric (test accuracy).

Optimizing hyperparameters for the DNN model used in ECG arrhythmia detection is possible using this function.

4.2.3 Phase 1: Exploration stage

Hyperparameter tuning is crucial to optimizing machine learning models for performance. Many optimization methods struggle with high-dimensional and complex solution spaces. The algorithms may struggle to maintain exploration-exploitation balance as dimensions rise, affecting their ability to find optimal solutions. This involves algorithms like PSO. This research part shows the Exploration Stage of a PSO method, which refines model parameters. Acceleration coefficients and random values drive iterative particle velocity modifications based on local and global optimum placements. This dynamic technique improves model performance, solution space navigation, and accuracy. PSO exploration efficiently explores the solution space and POA's resilience in varied optimization settings. Formula for updating velocity: Eq. (5)

$$\begin{aligned} Velocity_{i(t+1)} = w * velocity_{i(t)} + c1 \\ * r1\left(best_{position_i} - position_i\right) \\ + c2 * r2(best_{global_{position}} \\ - position_i) \end{aligned} \tag{5}$$

Here:

- $Velocity_{i(t+1)}$ denotes the updated velocity of particle i in iteration t+1.
- w represents the inertia weight.
- $velocity_{i(t)}$ is the current velocity of particle i in iteration t.
- $c1$ and $c2$ stand for cognitive and social coefficients, respectively.
- $r1$ and $r2$ are random values within the range [0, 1].
- $best_{position_i}$ refers to the best position found by particle i so far, $position_i$ represents the current position of particle i and $best_{global_{position}}$ denotes the best position found by any particle in the swarm.

Due to its tendency to converge swiftly to local optima, PSO generally struggles with multimodal problems. PSO's exploration of numerous peaks is limited, potentially disregarding better global solutions. This can limit its solution space exploration, making it harder to find the optimal solutions across varied peaks or optima. Thus, enhancing performance in complicated situations requires tweaking PSO to negotiate various terrain or adopting hybrid approaches.

4.2.4 Phase 2: Exploitation stage

Supplemental optimization methods like the POA help PSO handle multimodal difficulties. POA navigates many optima by exploring rather than exploiting, unlike PSO. To address PSO's premature convergence and improve global optimal solutions in multi-peak scenarios, the hybridization includes POA's properties into the optimization process. PSO and POA increase optimization's exploration-exploitation balance in this joint technique. Eq. (6) depicts exploitation.

$$new_{position_i} = Position_i + Velocity_i + 0.2 * \left(1 - t\frac{1}{max_{ilterations}}\right) * (2 * random.rand(D) - 1) * new_{position_i} \quad (6)$$

This formula updates the new position ($new_{position_i}$) if each particle in an iterative loop based on its current position ($Position_i$), velocity ($Velocity_i$) and other parameters as described.

This hybrid strategy uses PSO and POA to maximize their strengths. PSO's exploration efficiency compliments POA's exploitation resilience. This integrated strategy seeks to balance and improve hyperparameter tweaking.

4.2.5 Termination

The optimization process stops when the specified maximum number of iterations is reached. This condition prevents the algorithm from running indefinitely and ensures it stops after a certain number of iterations, regardless of convergence.

4.3 Cross-validation

Performed k-fold cross-validation on the training set to assess the generalization ability of the models and evaluated the models' performance metrics such as accuracy, precision, recall, F1-score, and area under the receiver operating characteristic curve (AUC-ROC) for each fold.

5. EXPERIMENTS RESULTS AND DICUSSION

5.1 Development and testing environments for deep PSO-POA model framework

The model, built on Python 3.7 using Keras 2.5.0 and TensorFlow 2.5.0, thrived in Kaggle's environment. Powered by an NVIDIA GeForce RTX 2060 GPU and an Intel Core i7-9750H CPU with 31.92GB RAM, it handled complex data effortlessly. This blend of top-notch software and high-performance hardware enabled smooth development, testing, and rigorous optimization tasks on Kaggle's platform.

Algorithm 1: Optimizing Classifier Hyperparameters through a Deep PSO -POA Optimization.

Input :

max_iterations: Maximum iterations

num_particles: Number of particles

Constants: acceleration_coefficient1, acceleration_coefficient2 (c1, c2)

inertia_weight: Inertia weight (w)

search_space_min, search_space_max: Search space boundaries

objective_function(): Evaluates the proposed deep learning model (ResIncept model, VGGRes model, InceptVGG, and LenetAlexLSTM) for arrhythmia detection

Phase 1: Exploration Stage

for t in range(max_iterations):

for i in range(num_particles):

$cognitive_{component} = acceleration_{coefficient1} * r1 * \left(best_{position_i} - position_i\right)$

$social_{component} = acceleration_{coefficient2} * r2 * \left(best_{global_{position}} - position_i\right)$

$velocity_i = inertia_{weight} * velocity_i + cognitive_{component} + social_{component}$

End of Particle Loop

End of Iteration Loop

Phase 2: Exploitation Stage

for t in range(max_iterations):

for i in range(num_particles):

initialize_population() # Using chaotic sequences

$new_{position_i} = position_i + velocity_i + 0.2 * (1 - t/\max\_iterations) * (2 * random.rand(D) - 1) * new_{position_i}$

$new_{position_i} = clip(new_{position_i}, search\_space\_min, search\_space\_max)$

new_fitness_i= objective_function(new_position_i)

if new_fitness_i> best_fitness_i:

best_position_i= new_position_i

best_fitness_i= new_fitness_i

End of Particle Loop

End of Iteration Loop

Best hyperparameters and corresponding fitness values optimized for the proposed deep learning model tailored for arrhythmia detection.

5.2 Parameters

As previously mentioned, the proposed model's functionality depends on specific parameters dictated by the

Multi Modal dataset and the configurations governing the PSO and POA algorithms followed by the DNN models in the framework. The count of evolutions, population size, neural network depth, kernel size, and number of neurons are crucial characteristics. The PSO metaheuristic algorithm requires inputs beyond coefficients and vectors, as seen in algorithm 1. It needs particle population size and evolution count. Table 4 contains experimental data for the suggested model.

Table 4. Variables and values in proposed optimization algorithm

Variable	Explanation	Value
`num_pelican`	The optimization population's pelican count.	5
`num_iterations`	Specifies the total number of iterations for the optimization process.	20
`t`	Current optimization iteration or time step.	5
`MaxT`	Maximum optimization algorithm iterations.	20
`w`	The inertia weight controls the current's response to past velocity.	0.5
`c1`, `c2`	Denote PSO algorithms' cognitive and social coefficients influencing particle mobility.	2.0
`history`	Historical data list used to track optimization process performance.	[]
`r1`, `r2`	Generate random numbers between 0 and 1 for PSO's velocity computations.	Random

When configured, these parameters control optimization. Num_pelican, num_iterations, t, and MaxT all effect optimization efficiency and population size. These factors impact search space exploration and algorithm convergence to optimal solutions. These variables affect PSO algorithms. w, c1, and c2 effect exploration and exploitation, whereas r1 and r2 randomly move particles. The history list tracks fitness values or other indicators across iterations to display optimization progress.

Optimizing the performance of machine learning models often involves fine-tuning various hyperparameters. Here is a breakdown of key parameters and their respective input ranges, outlining the scope for optimization in table. These parameters play a pivotal role in enhancing the model's efficiency and predictive power.

From the Table 5 by strategically navigating within the specified input ranges, there lies an opportunity to fine-tune and calibrate the model, aiming for heightened accuracy, faster convergence, and robust generalization.

Table 5. Hyperparameter search space ranges

Parameter Range	Input Range (Default)
Num Epochs	[20, 30, 40, 50, 100]
Learning Rate	[0.0001, 0.1]
Batch Size	[5, 10, 15, 20]
Hidden Units	[16, 32, 64, 128]

Rationale for Selection: The selection of these hyperparameters was based on a combination of domain knowledge, empirical evidence from previous studies, and extensive experimentation on our dataset. Our goal was to identify configurations that balance model complexity, convergence speed, and generalization ability, ultimately maximizing performance on the target task.

5.3 Performance metrics

5.3.1 Metrics used

In the context of Arrhythmias ECG Classification, these metrics are significant for evaluating model performance. Sensitivity represents the rate of correctly identified positive arrhythmia cases, while Specificity measures the rate of correctly identified negative cases. Precision denotes the positive predictive value specifically for arrhythmias classification. AUC Score is the Area Under the Receiver Operating Characteristic curve, demonstrating the model's discrimination ability. Loss typically indicates the model's performance in terms of error between predicted and actual values. Apart from these training times is also considered as the performance metrics to evaluate the running time of proposed algorithm.

5.3.2 Training time

Table 6 shows subtle model preferences from hyperparameter optimization. With a learning rate of 0.01, 64 epochs, 128 hidden units, and 20 batches, the ANN balanced accuracy and efficiency. ResIncept and VGGRes preferred 0.1 learning rate, moderate epochs, and smaller batches. Due to settings, AlexNet and ResNet-50 took longer to train. Hyperparameter selection directly affects model performance and computing efficiency across varied architectures, as shown in this work.

Table 6. Best hyper-parameter search and training time taken by each model for optimization

Model	Best Hyper Parameter Search			Epochs	Training Time
	Learning Rate	Batch Size	Hidden Units		(in s)
ANN	0.01	64	128	20	1000
Lenet-5	0.033	32	32	30	987
AlexNet	0.005	64	64	20	1851
VGG-16	0.001	32	64	30	1781
Inception	0.001	128	64	30	1890
LSTM	0.001	64	32	20	1684
Resnet-50	0.001	64	32	20	1871
ResIncept	0.1	64	32	20	1900
VGGRes	0.1	128	64	20	1872
InceptVgg	0.039	128	64	20	1789
LenetAlexLSTM	0.001	64	32	20	2001

Table 7. Training data performance analysis

Models	Accuracy(%)	Sensitivity (%)	Specificity (%)	AUC Score(%)	Loss (%)
ResIncept Model	96.40	78.61	28.04	81.07	11.9
VGGRes Model	97.39	82.13	31.91	82.61	10.1
InceptVGG	96.86	89.18	38.45	88.12	10.8
LenetAlex LSTM(LA-LSTM)	95.89	80.12	21.61	79.85	12.7

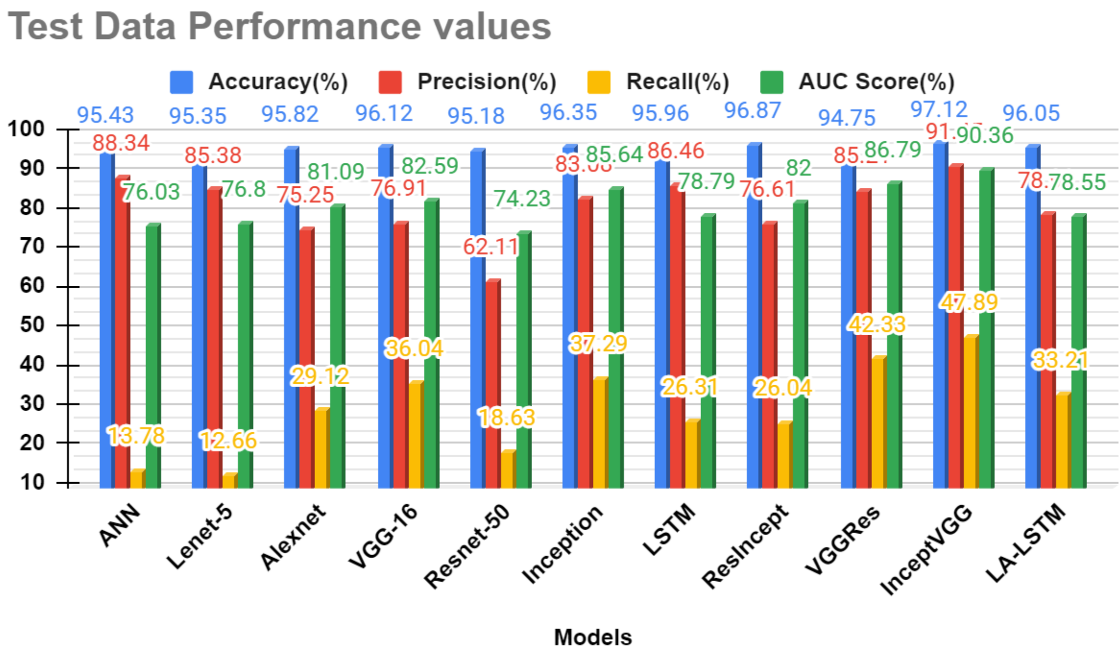

Figure 3. Testing data performance matrices taken by each model for optimization

5.3.3 Training data performance metrics

The array of performance metrics across various models showcases nuanced strengths in arrhythmia detection which is tabulated in Table 7. Models like Inception and InceptVGG exhibit remarkable accuracy (96.39% and 96.86%, respectively) coupled with strong AUC scores (86.54% and 88.12%, respectively), indicating superior overall performance. In contrast, VGG-16, VGGRes, and Resnet-50 demonstrate noteworthy precision and recall rates, achieving a balance between accuracy and precise identification. However, models like ANN and Lenet-5 reveal lower recall percentages, suggesting potential lapses in identifying relevant arrhythmia instances despite high overall accuracy.

5.3.4 Testing data performance metrics

The evaluation of the testing dataset from the Chapman-Shaoxing 12-lead ECG Database reveals diverse performance traits among models in arrhythmia detection as shown in Figure 3. The InceptVGG model stands out with exceptional accuracy (97.12%), high sensitivity (91.45%), and reasonable specificity (47.89%). Inception shows balanced performance with good sensitivity (83.08%) and specificity (37.29%). Models like ResNet-50 exhibit limitations in accurately detecting positive instances, while VGGRes strikes a promising balance between sensitivity (85.21%) and specificity (42.33%). These results underscore the importance of model selection aligned with specific clinical needs, emphasizing accurate detection while minimizing false positives or negatives in arrhythmia identification.

5.3.5 Comparative analysis

The classification of cardiac arrhythmia is essential for the prompt identification and management of cardiovascular disorders. Various techniques have been suggested in recent years to improve the precision and effectiveness of categorization systems. The purpose of this comparison is to evaluate the performance of current systems in contrast to our proposed method, which utilizes a novel technique called Deep PSO-POA for NN to aid in classifying cardiac arrhythmias. Table 8 summarizes the latest advancements in the classification of cardiac arrhythmia within the last 5 years. The comparative analysis examines various factors, including the year of publication, the databases employed, the number of cardiac arrhythmia classes, the status of data balance, the data size, the algorithms utilized, the level of achieved accuracy, and the ability of each proposal to automatically derive the framework.

Existing systems. CNN-HP evaluates six 1D MIT-BIH ECG signal groups [70]. It lacks automated architecture despite 95.3% accuracy. In this study, MITDB and a DNN with a recurrent neural network classify 2D image ECG data into three categories [71]. Without an automated basis, it possesses 96.7% precision like study [72]. This study [73] uses 5 MITDB 1D ECG signal classifications. We combine PSO and convolutional neural networks. While 94% accurate, it is not automated. IoT device 1D ECG signals are analyzed using an adaptive activation function and feedforward artificial hydrocarbon networks with deep learning [73]. Model

Farmland Fertility Algorithm with Hybrid Deep Learning (AAC-FFAHD DL). Excellent 97.76% correctness, but no automatic framework generation like earlier sources. Our cardiac arrhythmia classification is new. Recommended approach uses multi-modal database with 27 1D ECG signal classifications. Deep PSO-POA neural network innovation. A unique automatic hierarchical structure determination method boosts its 97.12% accuracy.

Comparative analysis with benchmark dataset. The Table 9 presents a comparison between proposed optimization techniques applied to the classification models using the benchmarked PTB-XL dataset.

InceptVGG demonstrates the highest accuracy (96.13%) along with the highest sensitivity (75.39%) and specificity (89.67%), making it the standout performer among the proposed model on the PTB-XL dataset.

Table 8. Comparative analysis with existing system

References	Database	No. of Classes	Method	Accuracy	Automated Framework
[70]	MIT-BIH	6	CNN-HP	95.3%	No
[71]	MITDB	3	DNN-RNN	96.7%	No
[72]	MITDB	5	H-PSO-CNN	94%	No
[73]	IOT Sensed Data	2	AAC-FFAHD & DL Model	97.76	No
Proposed Method	Multi modal database	27	Deep PSO -POA for NN	97.12%	Yes

Table 9. Proposed model vs PTB-XL dataset performance

Dataset	Model	Accuracy	Sensitivity	Specificity
PTB-XL	ResIncept Model	96.87	62.32	89.39
	VGGRes Model	95.95	60.17	86.19
	InceptVGG	96.13	75.39	89.67
	LenetAlex LSTM	96.12	69.28	89.28

Table 10. Existing method vs proposed method

System	Dataset	Model	Accuracy	Recall	Precision
Existing-TPE Optimization [74]	Georgia ECG	ResIncept Model	94.81	24.0	78.58
		VGGRes Model	94.04	11.9	66.67
		InceptVGG	95.02	35.4	70.71
		LenetAlex LSTM	94.77	28.1	71.14
Proposed-Deep PSO-Pelican Optimization	Georgia ECG	ResIncept Model	96.39	35.5	88.18
		VGGRes Model	95.48	20.6	75.12
		InceptVGG	95.73	24.1	79.11
		LenetAlex LSTM	96.07	30.9	83.57

Comparison to existing methods on standard benchmarks. The provided Table 10 presents a comparison of performance metrics and epoch periods for different models, utilising both the current TPE Optimisation and the suggested Deep PSO-Pelican Optimisation techniques, on the Georgia ECG dataset.

Specifically, the proposed ResIncept Model achieves the highest accuracy of 96.39%, with significantly improved recall and precision values of 35.54% and 88.18% respectively, showcasing the effectiveness of Deep PSO-Pelican Optimization in enhancing model performance. Overall, the results underscore the potential of optimization techniques like Deep PSO-Pelican Optimization in advancing the performance of machine learning models for medical applications such as ECG analysis.

Results of analysed hyperparameter sensitivity. Sensitivity analysis in neural networks involves assessing the impact of input variables on the output. The sensitivity analysis for the selection of hidden units involves evaluating the importance of input and hidden units in neural networks. This analysis helps identify the relative contribution of these units to the network's output. Below we have a basic representation to train the model based on sensitivity analysis of number of hidden units.

Step 1 : Train the proposed neural network with a specific number of hidden units.

Step 2 : Evaluate the trained model on a validation dataset to obtain the accuracy.

Step 3 : Repeat steps 1 and 2 for different numbers of hidden units.

Step 4 : Plot the accuracy against the number of hidden units.

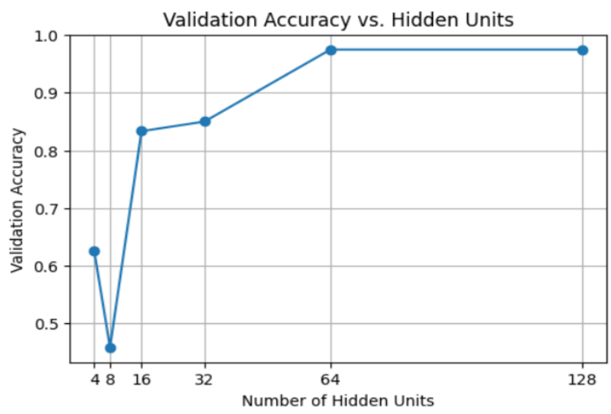

Figure 4. Validation accuracy vs hidden units

The Figure 4 shows the validation accuracy performed on Chapman-Shaoxing 12-lead ECG Database with hidden units ranges from [4, 8, 16, 32, 64, 128] to perform sensitivity analysis. Based on the provided dataset and the plotted graph:

(1). Initial Performance Fluctuation: With a low number of hidden units, validation accuracy fluctuates, indicating the model's instability or underfitting due to insufficient complexity.

(2). Improved Performance: Validation accuracy generally improves as the number of hidden units increases up to a certain point (around 64 hidden units in this case).

(3). Optimal Complexity: The peak validation accuracy of 97.5% is achieved with 64 and 128 hidden units, indicating an optimal level of complexity for this particular dataset and model architecture.

Distinctive features.

Database Diversity: Our suggested system differentiates itself from existing techniques by utilizing a multi-modal database, which guarantees a broader dataset compared to the prevailing use of MITDB or IoT-sensed data.

Cardiac Arrhythmia Classification: Unlike current methods that can only handle a small number of cardiac arrhythmia classes (ranging from 2 to 6), our suggested method showcases its strength by effectively classifying a significant 27 classes. The system's increased coverage improves its potential to be used in real-world situations where a wide variety of arrhythmias may be encountered.

Automation Capability: The suggested system is notable for implementing an automated framework for creating the layered architecture. This feature fills a notable deficiency in previous techniques, offering a more effective and user-friendly manner for constructing cardiac arrhythmia categorization algorithms.

Our approach is unique since it uses Deep PSO-POA for NN. This novel approach improves accuracy and refinement beyond previous methods. Compared to other methods, our solution, which uses Deep PSO-POA for NN on a multi-modal database, is more accurate and presents an automated architecture framework. The system's ability to manage more cardiac arrhythmia types, varied database use, and creative methodology advances categorization. Our technique helps detect and treat cardiovascular problems accurately and efficiently, aligning with current healthcare technologies.

5.3.6 Addressing hyper-parameter tuning complexity with PSO-pelican framework

The PSO-Pelican framework offers a novel solution to the complexity of hyperparameter tuning in deep learning models. By combining PSO with Pelican Search Optimization, the framework efficiently explores the hyperparameter space to identify optimal configurations that maximize model performance.

Key Features of PSO-Pelican Framework:

Exploration Stage: During the exploration stage, the PSO-Pelican framework leverages PSO to explore the search space and exploit local optima. Each particle represents a potential solution in the hyperparameter space, and its movement is guided by both personal best and global best positions.

Exploitation Stage: In the exploitation stage, the framework transitions to Pelican Search Optimization, which utilizes chaotic sequences to further explore and exploit promising regions of the search space. This adaptive strategy enables the framework to escape local optima and discover more optimal hyperparameter configurations.

Dynamic Adjustment: The framework dynamically adjusts the exploration and exploitation strategies throughout the optimization process, balancing between exploration of diverse hyperparameter configurations and exploitation of promising regions to refine the search towards optimal solutions.

5.3.7 Discussion

Our research delves into ECG-based arrhythmia detection, shedding light on the model's strengths and critical considerations. These insights have the potential to revolutionize the accuracy and efficacy of diagnosing arrhythmias in healthcare settings.

(1) Addressing the Challenges of Multimodal Optimization

Arrhythmia diagnosis is difficult because there are numerous arrhythmic patterns and optimal approaches. The hybrid method navigates terrain with many optimal options using PSO and POA. New solutions are PSO's specialty. POA efficiently uses current solutions. POA increases trade-offs between exploration and exploitation. These qualities allow the model to detect frequent and rare arrhythmias in complex and irregular environments.

(2) Possibility of Enhanced Hyperparameter Optimization

Adding logistic chaotic mapping enhances hybrid approach hyperparameter optimization. Chaotic mapping enhances PSO-PAO startup and exploration. This improves arrhythmia detection models' reliability. Arrhythmia detection model performance depends on hyperparameter tweaking. The PSO-POA hybrid's hyperparameter optimization lets researchers and doctors adjust model parameters based on dataset features. Adaptability helps with patient populations' dynamic and diverse arrhythmia patterns.

(3) Relevance for Medical Practice

The research could revolutionize arrhythmia detection in clinical practice by enhancing reliability through advanced investigation, multimodal optimization, and hyperparameter tuning. The PSO-POA hybrid significantly reduces false detections, enabling faster, more accurate decisions for improved patient outcomes.

(4) Comparative Analysis of Existing Models

Comparing the PSO-POA hybrid method to different arrhythmia detection methods helps determine its genuine impact. This involves comparing performance to standard machine learning, deep learning, and other optimization strategies. Analyzing the PSO-POA hybrid's pros and cons would assist evaluate its role in arrhythmia identification. Understanding how the proposed strategy improves current models is crucial for clinical research practice.

To summarize, the conversation emphasizes the PSO-POA hybrid method's significant capacity to revolutionize arrhythmia diagnosis using ECG data. The suggested model significantly advances the development of automated arrhythmia detection systems in healthcare by addressing exploration problems, multimodal optimization difficulties, and enhancing hyperparameter tuning. The significance for clinical practice highlights the necessity of ongoing study in this area, emphasizing tackling obstacles, verifying applicability, and carrying out thorough comparative analyses.

While our study illuminates numerous advantages, it also brings forth significant drawbacks and considerations.

- **Real-time Implementation Challenges:** The model's complexity may impede its seamless integration into clinical settings, posing challenges for real-time applications critical to healthcare.
- **Interpretability Limitations:** Deep learning models often lack interpretability, posing challenges in comprehending and justifying decisions. This limitation could

hinder acceptance in critical healthcare scenarios where interpretability is paramount.

- Potential for Overfitting: Although our framework demonstrates promising results in the evaluated datasets, there is a risk of overfitting, particularly when applying the model to new or unseen data. Careful validation and robustness testing are essential to mitigate this risk and ensure the generalizability of our findings.

Despite the potential benefits of our framework, its integration into existing clinical workflows may present logistical and operational challenges.

By comparing these findings to our study goals, we see the need for future studies to simplify models and improve interpretability without sacrificing accuracy. Despite limitations, this research shows promise for arrhythmia identification, but it needs to be refined to meet actual healthcare needs.

6. CONCLUSION AND FUTURE WORK

The PSO-Pelican Arrhythmia Optimize (PSO-POA) hybrid technique and autorhythmic model have showed potential in automating deep learning parameter fine-tuning to improve arrhythmia identification. The study found a promising balanced exploration-exploitation hyperparameter optimization strategy. Chaotic initialization and synergistic PSO-POA interactions are used in this technique. InceptVGG's extraordinary precision, sensitivity, and specificity across varied datasets shows that high-performing models can be used in healthcare. InceptVGG excels with 97.12% accuracy and 91.45% sensitivity. This major development improves cardiac arrhythmia categorization. These discoveries may help doctors make accurate diagnosis and create effective treatment programme. These models can transform arrhythmia diagnosis by providing accurate and rapid data to doctors. After theoretical advancements, the research emphasizes the need for accurate arrhythmia detection devices. InceptVGG and similar models satisfy the primary research goal of improving arrhythmia identification accuracy. These models may modify clinical settings, making them important outside academia. However, the voyage continues. Future research should build on this foundation and focus on many key factors to advance arrhythmia detection. It is crucial to conduct thorough empirical validations of the proposed approach on various datasets and problem domains to ensure its effectiveness and applicability. Although the work has demonstrated encouraging outcomes, more verification using a wider variety of datasets would improve the applicability of the suggested hybrid approach. Ensuring the model's stability and performance across varied patient demographics and variations in arrhythmia is of utmost importance at this step.

(1) Adaptive Parameter Tuning: The hybrid method requires further study. The hybrid approach's parameter flexibility should be optimized in future research. This inquiry may involve real-time adjustments based on input data features to improve optimization performance and adaptation to diverse arrhythmia patterns.

(2) The capacity of the PSO-POA hybrid technique to handle more complicated problem spaces is an area that needs further investigation. Given the complicated nature of arrhythmia detection, ensuring that the proposed approach can handle more intricate data patterns is essential to be considered reliable and effective.

(3) Model Refinement and Expansion: Although InceptVGG has performed well, it is important to continue improving and expanding its capabilities. Alterations, extensions, or combinations with other architectures may offer additional benefits. Innovative neural network architectures for arrhythmia identification may also increase the model's performance.

(4) Ethical Considerations and Real-World Implementation: As these models become realistic, ethics become crucial. To ensure ethical healthcare implementation of automated arrhythmia detection systems, further investigations should focus on data confidentiality, system explanation, and unfairness.

Essentially, the PSO-PAO hybrid technique has successfully reached high accuracy rates, especially when using InceptVGG. This result paves the way for further research in a dynamic and expanding subject. The intended future directions aim to enhance, expand, and consolidate the hybrid optimization methodology, enhancing arrhythmia detection systems' accuracy, efficiency, and practicality. This study stimulates continuous efforts to improve healthcare outcomes by utilizing state-of-the-art technology and creative methods for detecting arrhythmia.

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