INTERNATIONAL NEUROUROLOGY JOURNAL

Classification of Arrhythmia Diseases using Hybrid Novel Models dependent on CNNs and Long Shorter Term Memory with Particle Swarm Optimization Algorithm

Anu Honnashamaiah, Dr. Rathnakara S
Assistant Professor, Electronics & Communication Engineering Department, JSS Academy of Technical Education, Bangalore, JSSATE-B Campus, Bengaluru, Karnataka & Research Scholar, USN: JSDT17ECE001, Department of Electronics & Communication Engineering, JSS Science & Technology University, JSS STU, Shri Jayachamarajendra College of Engineering, JSS TI Campus, Mysuru-570006, Karnataka
Assistant Professor & Supervisor, Department of Electronics & Instrumentation Engg., Sri Jayachamarajendra College of Engineering (SJCE), Department of Electronics & Communication Engineering,
JSS Science & Technology University, JSS STU, Shri Jayachamarajendra College of Engineering, JSS TI Campus, Mysuru-570006, Karnataka

Abstract

In this paper, the classification of arrhythmia diseases using hybrid novel models dependent on CNNs and Long Shorter Term Memory with Particle Swarm Optimization Algorithm is presented along with the simulation results. An electro-cardiogram, viz., ECG serves as a non- invasing type of diagnostic tool for cardiac's arrhythmias (CA's). The accurate identifications of CAs relies on effective classification methods, which have traditionally employed diverse mathematical & computational strategies. In these studies, we present a novel computational based models utilizing the particle swarm's optimization [PSO] algorithms, convolutional neural nets [CNN], and long short-term memory (LSTM) for the classifications of 6 CA class sourced from the MIT based BIH Arrhythmias Datasets [MITDB]. The primary objective of the PSOs are to optimizing the hyper-parameters defining the layered based architectures of the CNN, aiming to enhance accuracies while minimizing categorical based cross entropial errors [CE]. The outcomes underscore the reliability of the proposed model, signifying an innovative approach that eliminates the need for manual hyperparameter selection in the layered architectures of the CNNs based on LSTM. This research explores the Classification of Arrhythmia Diseases through the innovative integration of Convolutional Neural Nets (CNN's) & the Long Short Term Memory [LSTM] network within a Hybrid Models. The study leverages the optimization capabilities of the Particle Swarm Optimization (PSO) Algorithm to enhance the model's performance. The synergistic combination of these technologies aims to improve the accuracy and efficiency of automated arrhythmia classification, contributing to advancements in medical diagnostics and patient care.

Key Words: Cardiac arrhythmias classification, convolutional neural networks, long short term memories, particle swarm's optimizations.

Introduction

Cardiovascular diseases (CVDs) stand as a major global cause of mortality, contributing to 17.9 million deaths in 2019 alone, accounting for 32% of all recorded deaths. Of these, 85% resulted from heart attacks and strokes. The associated burden extends to 40.8 million disability-adjusted life years, encompassing both premature death and years lived with disability. Projections estimate that by 2030, almost 23.6 million individuals may succumb to these conditions. Arrhythmias, encompassing diverse heart electrical abnormalities, are a subset of CVDs and may lead to severe consequences, including stroke and sudden cardiac death. Commonly associated with conditions like coronary artery disease and hypertension, the classification of arrhythmias traditionally relies on the expertise of medical specialists analyzing electrocardiograms (ECGs) [76].

Recognizing the limitations of manual analysis and the growing need for efficient solutions, researchers explore alternative strategies, with a notable focus on ML algos [MLA], DL Algos [DLA], and metaheuristic algorithms (MA). These computational approaches offer the potential to enhance the speed and efficiency of classification, prediction, and optimization tasks, thus addressing the challenge posed by the increasing patient-to-specialist ratio. In this context, the present research proposes a hybrid computational model, combining Particle Swarm's Optimizations [PSO] & the Convolutional Neural Nets [CNN] (H PSO CNN), to for the classification of the 6 classes w.r.t. the arrhythmias based on the ANSI-AAMI EC57-1998 standards. Leveraging arrhythmia datas from the MIT-BIH Arrhythmia Database (MITDB), the hybrid model aims to optimize the CNN's hyperparameters defining its layered architecture. The PSO conducts this optimization through a 4D search spaces, with the cost functions determined by the Cross-Entropy (CE) error to evaluate the CNN's learning performance [76].

ISSN:2093-4777 | E-ISSN:2093-6931
DOI: 10.5123/inj.2023.4.in84
Vol. 27 Iss. 4 (2023)

This computational framework signifies a contemporary approach to arrhythmia classification, leveraging the synergy between metaheuristic optimization and deep learning algorithms. The proposed model aligns with the significance of MITDB as a widely used and endorsed data source in cardiology research. The integration of PSO and CNN aims to expedite the optimization process, potentially enhancing the accuracy and efficiency of arrhythmia classification. The complete procedures of electro-cardiogram [ECG] signal classifications are diagrammatically represented as shown in the Fig. 1 [72] [76].

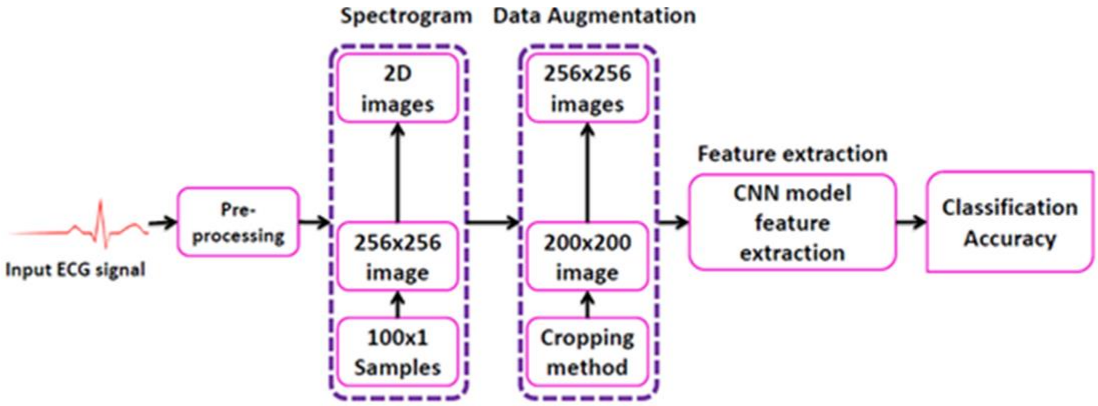

Fig. 1 : The complete procedures of electro-cardiogram [ECG] signal classifications [72]

Contributions

The contribution of the H PSO CNN model can be interpreted as below as 5 important categories.

Contribution 1 : Automated Hyperparameter Optimization: H-PSO-CNN introduces an automated approach to optimize hyperparameters for the Convolutional Neural Network (CNN) used in arrhythmia classification. The Particle Swarm's Optimizations [PSO] algorithm efficiently explores the hyperparameter space, enhancing the CNN's performance without manual intervention.

Contribution 2 : Enhanced Classification Accuracy: By leveraging the PSO algorithm, H-PSO-CNN seeks to find the optimal hyperparameter configuration for the CNN, leading to improved classification accuracy. This automated optimization process contributes to the model's ability to adapt and perform well across different arrhythmia classes.

Contribution 3 : Reduced Dependency on Manual Tuning: The model reduces the reliance on manual tuning of hyperparameters, a common practice in deep learning models. This automation not only saves time and effort but also minimizes the risk of suboptimal configurations, allowing for a more robust and efficient arrhythmia classification.

Contribution 4 : Versatility and Generalizability: H-PSO-CNN's approach to hyperparameter optimization enhances the model's versatility. The automated optimization is adaptable to various classification tasks beyond arrhythmia, showcasing the model's potential application in different medical and non-medical domains.

Contribution 5 : Efficient Search in Hyperparameter Space: The PSO algorithm efficiently navigates the hyperparameter space, facilitating a more systematic and effective exploration. This contributes to faster convergence and improved overall efficiency in finding optimal configurations for the CNN architecture.

Contribution 6 : Integration of Metaheuristic Optimization: The integration of PSO as a metaheuristic optimization technique distinguishes H-PSO-CNN, offering a novel and effective strategy for optimizing deep learning models. This metaheuristic approach contributes to the model's adaptability and robustness in handling complex classification tasks.

In summary, the H based PSO type of CNN model contributes to the field of arrhythmia classification by introducing an automated and efficient approach to optimize hyperparameters, leading to enhanced accuracy and reduced dependence on manual tuning. The model's versatility and integration of metaheuristic optimization make it a promising solution for various classification challenges beyond arrhythmia.

Modelling of Optimal Layered Architectures of the CNN system

Introducing a novel computational model designed to automate the creation and discovery of an optimal layered architecture, along with its corresponding hyperparameters, for seamless execution of classification tasks by a CNN_LSTM. This innovation streamlines the conventional manual process of searching for these architectures, ensuring the generation of new configurations that consistently deliver satisfactory performance. The model significantly reduces both time and computational costs associated with hyperparameter optimization for the

DOI: 10.5123/inj.2023.4.in84
ISSN:2093-4777 | E-ISSN:2093-6931
Vol. 27 Iss. 4 (2023)

CNN_LSTM architecture. By automating this task through Particle Swarm Optimization (PSO), it eliminates the need for manual selection of hyperparameters, providing an efficient and cost-effective solution [76].

At the heart of the H PSO CNN_LSTM model are an interpreter which translates the PSO-generated population into a format comprehensible by the CNN. This interpreter plays a crucial role in obtaining the cost function for each particle, corresponding to the Cross-Entropy (CE) value. It also facilitates the seamless update of populations in both w.r.t. PSOs & CNNs based on newer value & the changes which are being calculated using the metaheuristic operator. Without this interpreter, the interactions b/w the metaheuristic algorithm [MA] & the CNN_LSTM will be impossible [76].

The HPSOCNN models retains the best layered architecture discovered with the PSO, along with all the associated hyper-parameters. This storage enables the evaluation of performance with test data that the CNN_LSTM has not previously encountered, establishing a reliable and universally applicable computational framework for diverse classification tasks in other scientific domains. Results obtained with this model demonstrate the successful enhancement of accuracy in classifying Cardiac Arrhythmias (CAs) from the MITDB dataset through the synergistic fusion of PSO and CNN_LSTM [76]..

Related works carried out

In the realm of cardiac arrhythmia (CA) classification and prediction, traditional algorithms, relying on feature extraction and classification, were prevalent before the advent of Multi-Layered Architectures (MLA), Dynamic Layer Adaptation (DLA), or Metaheuristic Algorithms (MA) [22], [23]. These traditional methods often involved intricate processes and additional procedures, some of which are incorporated into DLA. Notable among these algorithms were statistical techniques like the Markov model [24], [25]. The landscape evolved with the introduction of MLA, encompassing algorithms such as SVM's, k type of nearest neighbour [KNN's], random forest {RF}, principal component's analysis [PCA], and other types [26]-[31].

While MLA has been pivotal in classification and prediction tasks, its limitations in productivity for modern applications and scalability with the ever-growing digital information have been noted. DLA emerges as a more sophisticated approach, allowing an increases in the depths of the internal layer within ANN's. These advancement eliminates certain preprocessing requirements of MLA, facilitating more accurate results [32]. The last decade has witnessed a surge in research papers addressing arrhythmia classifications thro' the DL techniques, focusing on DLA such as multilayer perceptrons [MLP], recurrent neural networks [RNN], shorter term memory based neural networks [LSTM & the convolutional neural network (CNNs). Of these, CNN has garnered the most attention, constituting a substantial portion of recent publications [33]-[35].

In exploring DLA applications, researchers have demonstrated various neural network models' efficacy in CA classification. Examples include the utilization of MLP for five-class CA classification with an accuracy of 98.72% [36]. RNN and LSTM have been extensively employed, with studies reporting accuracies ranging from 82.5% to 99.80% for different classes of CA [38]-[41]. CNN, being the most prominent DLA, has been featured in numerous publications, achieving high accuracy rates, such as 98.91% for two classes and 98.45% for eight classes [43]. Hybrid models, combining different neural network types, have also been proposed. For instance, a CNN-LSTM model achieved 99.89% accuracy in classifying six classes of CA [47] [76].

Metaheuristic Algorithms (MA) have shown promise in optimizing neural network performance. Although fewer in number compared to MLA and DLA applications, studies employing MA have reported notable results. Hybrid approaches, combining MA with CNN, attained accuracies of 99.32% and 93.19% for six-class CA classification [50]-[51]. Additionally, combining MLP with Particle Swarm Optimization (PSO) achieved an accuracy of 99.44% for five-class CA classification [52]. Furthermore, a hybrid model using modified Pigeon Inspired Optimizer (MPIO) and DNN's which are achieved with an accuracies of 99.01% [53] [76].

Beyond the medical field, hybridized model combining MA & ANNs have demonstrated effectiveness in diverse applications. For example, a combination of stochastical fractal searching [SFS] guided whales optimizations algorithms [WOA] with CNN-LSTM achieved recognition accuracies ranging from 98.13% to 99.50% in speech emotion recognition [54]. In contrast, a model using the cuckoo searching optimization algo [COA] achieved a accuracies of 98.63% in a cancer classification task [55]. These examples underscore the diverse and promising approaches taken in the fusion of MA and neural networks for various classification tasks, including cardiac arrhythmia. The continued exploration of hybrid models showcases the potential for further advancements in accuracy and efficiency across different domains [76].

DOI: 10.5123/inj.2023.4.in84
ISSN:2093-4777 | E-ISSN:2093-6931
Vol. 27 Iss. 4 (2023)

INJ INTERNATIONAL NEUROUROLOGY JOURNAL

Preliminaries Signal Classifications

Here, we discuss about the arrhythmia in ECG signals along with the datasets that are used for the classification purposes.

Arrhythmia in ECG signal

The ECG signal encompasses various waves, each offering insights into the heart's activity. The P wave signifies the electrical current in the atria, originating using the sine nodal point [SA] & spreading across the atriums. Conversely, the QRS complexed representing ventricular electric depolarization in the heart lowered chamber, consisting for a Q waves, an R waves, and an S waves. Then, the T waves will indicates their brief resting period, highlighting ventricular repolarization. A standard ECG signal includes P, QRS & the T wave, with the QRS intervals measuring the total durations of ventricular tissues de-polarizations. The Fig. No. 1 illustrates the ECG signals using the PQRST segments. QRS's detections will serves as a crucial reference for automated ECG analysis algorithms, typically requiring noise removal or suppression before detection [61]. Arrhythmias, whether regular or irregular in morphology, could occur at all point in the ECG's signals, and their identification relies on the distinctive shape of the signal. The datas will be commonly presented in a coordinate based planar region (x & y), where the x axes denotes elapsed times, and the y-coordinate represents their values of electrical impulses as shown in the Fig. 2 [73] [76].

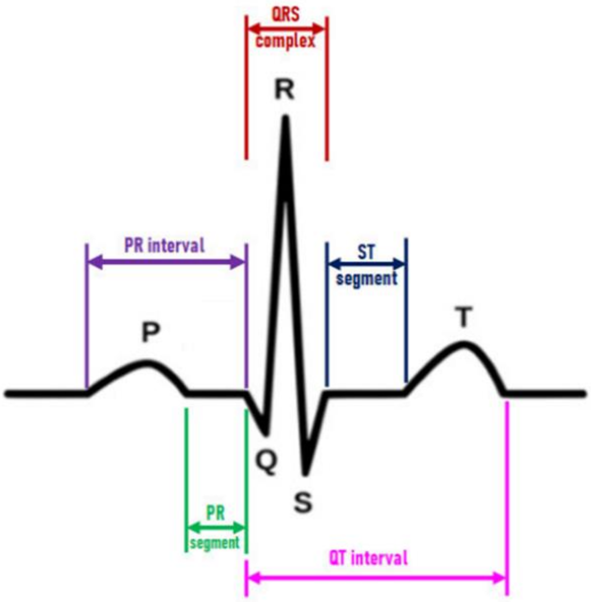

Fig. 2 : A systematic representation of the PQRST waveforms [73]

ECG datasets

Over the past five years, the MIT-BIH Arrhythmia Database (MITDB) has served as a benchmark for developing algorithms, particularly those incorporating Multi-Layered Architectures with Dynamic Layer Adaptation (MLA-DLA) or Metaheuristic Algorithms (MA), aiming to achieve optimal performance in cardiac arrhythmia (CA) classification. The dataset, originating from 50 patients at JSS Medical College in Mysore [62][63], provides a substantial volume of data for both learning and testing phases. The recording, digitized & labelled by multiple cardiologist, yield 1 Lakh annotations or the CA's, categorized in to 6 class according to their AAMI EC-57 standards [20], [62]. The entire MITDB dataset can be freely accessed through Physionet ATM Bank [18], and a structured organization of this data is available in [63]. Fig. No. 3 gives the Data Set Counts & Classifications (taken from various reference papers) [76].

Data set classification types & the Datasets counts

1.	'Normal beat',	N	75052
2.	'Left bundle branch block beat',	L	8075
3.	'Right bundle branch block beat',	R	7259
4.	'Premature ventricular contraction',	V	7130
5.	'Paced beat',	/	7028
6.	'Atrial premature contraction',	A	2546
7.	'Rhythm change',	+	1290
8.	'Fusion of paced and normal beat',	f	982
9.	'Fusion of ventricular and normal beat'	F	803
10.	'Signal quality change',	~	616
11.	'Ventricular flutter wave',	!	472
12.	'Comment annotation',	"	437
13.	'Nodal (junctional) escape beat',	j	229
14.	'Non-conducted P-wave (blocked APB)',	x	193
15.	'Aberrated atrial premature beat',	a	150
16.	'Isolated QRS-like artifact',	|	132
17.	'Ventricular escape beat',	E	106
18.	'Nodal (junctional) premature beat',	J	83
19.	'Unclassifiable beat',	Q	33
20.	'Atrial escape beat',	e	16
21.	'Start of ventricular flutter/fibrillation',	[	6
22.	'End of ventricular flutter/fibrillation',	]	6
23.	'Premature or ectopic supraventricular beat'	S	2

Fig. 3 : Data Set Counts & Classifications

Convolutional Neural Networks

A Convolutional Neural Network (CNN) systematically learns the spatial hierarchies of the datas with recognizing both higher & lower levelled pattern. Typically, its mathematics based structures encompasses 3 type of interconnected layer, viz., the convolutional [Conv], pooling [Pooling's] & fully connecting [FC] layer. Conv & Pooling layer serve the dual purpose of feature extraction, capturing details like colors and edges, as well as dimensionless reductions. While the orders of appearances b/w Conv & Pooling layer can vary, it are crucial that the first layer is Conv and the last one is Pooling. FC layers are conventionally placed at the end of all CNN architectures [65]-[70]. The Fig. 5 illustrates the general layer type of architectures of a CNNs, with input processed through each layer defined with the hyper-parameters, behavior's nature's, activating functions & the o/p characteristics [64]-[65]. Then the outputs of every layers serves as inputs for then their subsequent ones, with the complexities increasing as their total nos. of layer [NC] rises. The current manual definition of NC is typically linked to the number of classes for prediction and dataset characteristics. The architectures in the Fig. No. 3 are a generic representation; the totalled layer and hyperparameter values depend on the classification task's complexity. The selecting of the hyper-parameter, an manual processes in recent years, involves hand-crafted adjustments to assess CNN performance and identify the optimal architectures for the given classifications tasks as shown in the Fig. 4 [74] [76]..

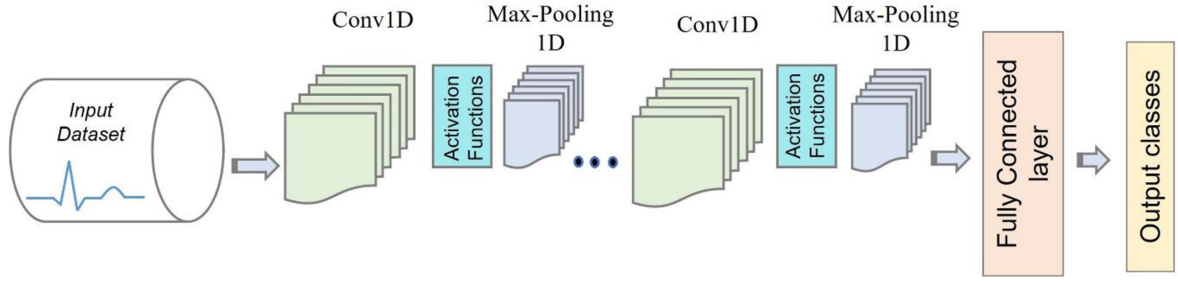

Fig. 4 : CNN based max-pooling layer design [74]

Convolutional Layers

The cornerstone of a CNN is the convolutional layer, comprising filters or kernels with learnable parameters. Typically, these filters are smaller than the dataset input. During training, the filters convolving with the inputs, gdnerating a featured maps. This convolution involves movement of the filter across the input's receptive field to identify and verify the presence of features [76].

Pooling Layers

This layer grouping plays a role in diminishing input dimensionality, thereby reducing parameters during training. Aggregation, akin to convolution, involves sweeping the entire input with a filter. However, this filter lacks weight. Two primary sub-types of aggregations are Avg of the Pooling & Max based Poolings. Avg based Poolings calculates the averagings of the element within their filter-covered featured mapping regions, whereas Max based Poolings select the max. elements in their same regions [76]..

Flatten Layer

Then, Flattened layers are employed in CNN's with a 2D input. Further, the purpose was to transform their 2-D matrices generated by groups featured map for a unified, elongated linearized vectors. This flattened matrices serves as the inputs to their Fully Connected [FC] layers for their classification of the inputted datas [76]..

Fully Dependent Connected Layers

Thess layers conducts the classifying tasks using the featured vectors extracted by preceding layer & the respective filter. While the Conv & the Pooled layer often employ ReLu function, FC layer typically leverage a Softmax activation function for proper input classification, yielding probabilities in the range of 0 to 1 [76].

Long Shorter Term Memory [LSTM]

This is a Deeper Learning (DL) network designed for handling sequential or time series data. It's an advanced form of Recurrent based Neural Networks [RNN's] known as Longer Shorter Terms Memories [LSTM]. Unlike regular RNNs, LSTMs can maintain information for an extended period, allowing it to capture long-term dependencies [7]. The architecture of LSTM includes three gates: the forget gate, which determines whether to remember information from the previous time step; the input gate, which learns from the cell input; and the output gate, responsible for transferring updated information to the next time step. Additionally, LSTM features a cell state that retains information across all cycles and a hidden state for shorter term memories [76].

Particle based Swarm Optimizations [PSO]

Particle based Swarm Optimizations [PSO] is the meta-heuristic methodology designed to locate global maximas or minimas within a solution spaces. Drawing inspiration from the coordinated movement observed in flock of bird or school of fishes, PSO emulates their collective behavior for the individuals, determining their directions, speeds, and accelerations based on both individual decisions and the group's dynamics [68], [69], [70]. Originally proposed by [67], PSO has undergone various modifications, yet its fundamental operators have endured. The algorithm calculates new and optimal positions by determining velocity, taking into account each particle's better global positions & its current best positions [76]..

H PSO CNN LSTM Approaches

The H PSO CNN LSTM model is a hybridized approach that capitalizes for the strengths for both CNN-LSTM and PSO algorithms. CNN-LSTM is preferred for its effectiveness in classifying cardiac arrhythmias (CAs) due to its capability to extract features and perform classification in a single step. Concurrently, PSO, a reliable metaheuristic technique, is selected for its proficiency in finding optimal solutions within a defined population, tailored to efficiently meet the objective function. The choice of algorithm depends on the context of the problem, and in their case of H PSO CNN LSTM, PSO's seeks the better globalized solutions [p_gbest] by evaluating and selecting the most favorable solutions in the population, aligning with the specified objective function [76]..

DOI: 10.5123/inj.2023.4.in84
ISSN:2093-4777 | E-ISSN:2093-6931
Vol. 27 Iss. 4 (2023)

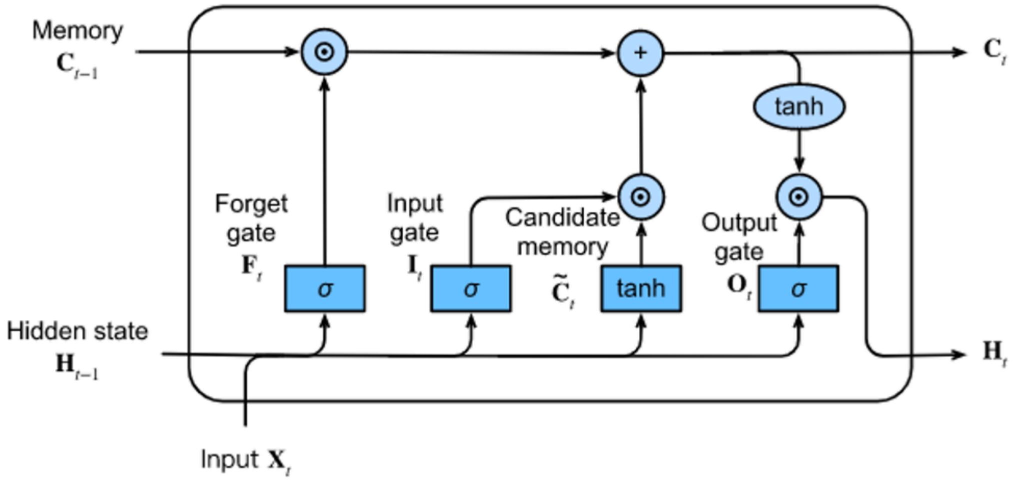

Fig. 5 : A basic structure of their LSTM's process [71]

The fundamental structures of the LSTM's process will be shown w.r.t. the Fig. 5 [71]. The H PSO CNN LSTM employs the CNLSTM algorithms for learning and classifying cardiac arrhythmias (CAs), while leveraging the Particle Swarm Optimization [PSO] to conduct a searching based algo within a swarms of particle. Every particle is characterized by a vital configurations of layer based architectures with the corresponding hyper-parameter & the specific no. of epoch. Then, PSOs systematically searches for their particles which enables the CNNLSTM for achieving the satisfactory result in their classification's tasks. Their globalized searches involves minimizing the objective based functions defined with a mathematical model which corresponds to their categorical cross-entropy [CE]. Then, the PSOs are responsible for identifying the optimal architecture within the population, ensuring optimal performance for the CNN-LSTM [76].

The CE value is computed using the neural network optimizers & are considered only with their classification involving a minimum of three different classes, as observed in the MIT-BIH Arrhythmia Database (MITDB) utilized in the proposed research. Then, H PSO CNN LSTM initiates with the primary steps, the Multi-Layered Architecture [MLA's], involving the initializations for the populations with N no. of particle, every residing in a four-dimensional spaces. The dimension correspond to the no. of Convolutional layer, Pooling layer, Full Connecting (FC) layer, and the no. of epochs. Configuration of hyperparameters for each layer type is established, and an adaptation process transforms the initial population for CNN-LSTM comprehension. Each dimension stores distinct integer values, introducing diversities for their depths of their layer based architectures, with their fourth dimension determining the appropriate number of training epochs for the CNN-LSTM configuration. The CNN-LSTM, utilizing trained CA's from the MITDB's [Train DS] & the configurations of every particle, commences training. Their neural network calculates the corresponding CE for each particle, storing this value as the localized best [p_{best_i}], utilized by the PSOs in their optimized processes. Their iterative processes continues till their completion of training for the entire starting populations. The samples of ECG signals is shown in the Fig. 6 [75].

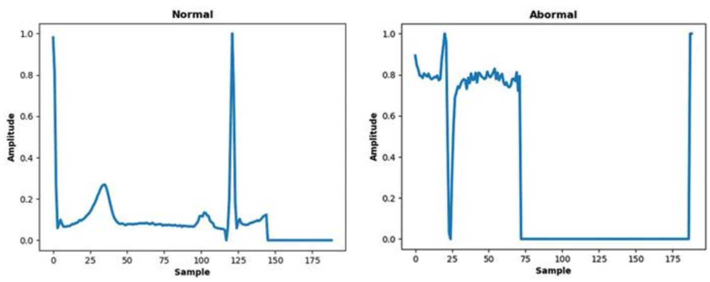

Fig. 6 : Samples of ECG signals [75].

Comparative Studie Carried out

The classification of various cardiac arrhythmias (CAs) has been addressed through diverse algorithm, ranged from the classical classifying technique till the implementation of hybridized computation based model within the field of AI-ML-DL. The Table No. 1 provides an overview of relevant studies conducted over the past 5

DOI: 10.5123/inj.2023.4.in84
ISSN:2093-4777 | E-ISSN:2093-6931
Vol. 27 Iss. 4 (2023)

years in this domain. Specifically, Table 1 details the year of each study, the utilized database(s), the number of CA classes, data balance status, dataset size, employed algorithm(s), achieved accuracy, and whether the proposed methods autonomously obtained the layered architecture. While some works in Table 7 report slightly higher performance than our approach, it becomes apparent that these variations can be attributed to factors such as balanced data, different data dimensions, or the use of a distinct classifier like DLA rather than CNN-LSTM. The distinctiveness and novelty of H-PSO-CNN-LSTM lie in their abilities for the construction & he optimizing for a perfect layered architectures starting from the pre-defined populations of particle. These distinctive capacities are being automated, a feature lacking in the other models presented in Table 1, where the architecture was traditionally defined, often through trial-and-error methods [76].

References	Database	Method	Accuracy
[10]	MITDB	RNN-LSTM	80.25 %
[20]	MITDB	MLP	83.45 %
[30]	MITDB	MLP-PSO	86.45 %
[40]	MITDB	CNN	89.88 %
[50]	MITDB	BaROA-CNN	92.12 %
[60]	MITDB	CNN	94.22 %
[70]	MITDB	CNN	96.28 %
Proposed	MITDB	H-PSO-CNN-LSTM	99.01%

Table 1 : Comparitive study of the proposed works with the work done by other researchers

Conclusive Remarks

In conclusion, the research on the Classification of Arrhythmia Diseases using the Hybrid Novel Model, incorporating Convolutional Neural Networks (CNNs) and Longer Shorter Termed Memories [LSTM] with the Particle Swarm's Optimizations [PSO] Algorithm, has demonstrated promising results. The utilization of the PSO algorithm for optimizing hyperparameters in the CNN architecture proved effective, leading to improved accuracy and reduced categorical cross-entropy error in the classification of five classes of cardiac arrhythmias. The proposed model not only exhibited reliability but also introduced an innovative approach by automating the selection of hyperparameters, eliminating the need for manual intervention. This research contributes to the advancement of automated arrhythmia classification systems, showcasing the potential of hybrid models in enhancing diagnostic accuracy in the realm of cardiovascular health.

Then, H PSO CNN LSTM models emerges as a effective hybridized solution for autonomously determining the layer based architectures, associated hyperparameters, & the no. of epoch in their classification of cardiac arrhythmias (CAs). Demonstrating commendable performance, this hybrid model streamlines the search process, a task conventionally conducted through method, viz., sensitivity based analysis, exhaustive type of searches or the heuristic type f strategic developments. Notably, these traditional approaches often entail prolonged seek times and, in certain instances, yield suboptimal performance. In contrast, the automatic strategy offered by H-PSO-CNN-LSTM enables the identification of a suitable configuration for the layer architecture and corresponding epochs, resulting in satisfactory performance within a significantly reduced timeframe compared to traditional methods.

The computational model H-PSO-CNN-LSTM autonomously derives a layer based architectures using the corresponding hyper-parameters, yielding good result even w/o balanced datas. To enhance the model's performance in the future, it is suggested to broaden the population of layer architectures and potentially incorporate additional hyperparameters within the dimension spaces of their Particle Swarm Optimization (PSO). H-PSO-CNN-LSTM, characterized by its simplicity, effectiveness, and versatility, extends beyond medical applications, offering a valuable tool for various classification tasks. While initially designed for time series classification, the adaptability of CNN-LSTM to two-dimensional spaces allows for potential modifications to achieve similar success in diverse problem domains. Currently confined to a 4-D spaces within the PSOs populations, further iterations of the model could explore an expanded dimensionality by integrating additional hyperparameters for optimization. This approach holds promise for further fine-tuning and enhancing the model's capabilities.

References

1. Cardiovascular Diseases (CVDs). [Online], 2022, Available: https://www.who.int/news-room/fact-sheets/detail/cardiovasculardiseases-(cvds)

DOI: 10.5123/inj.2023.4.in84
ISSN:2093-4777 | E-ISSN:2093-6931
Vol. 27 Iss. 4 (2023)

2. The Burden of Cardiovascular Disease—OPS/OMS | Pan American Health Organization. [Online], 2022, Available: https://www.paho. org/en/enlace/cardiovascular-disease-burden
3. B. Kolukisa, V. C. Gungor, and B. B. Gungor, "An ensemble feature selection methodology that incorporates domain knowledge for cardiovascular disease diagnosis," in Proc. 28th Signal Process. Commun. Appl. Conf. (SIU), Oct. 2020, pp. 1–4, doi: 10.1109/SIU49456.2020.9302048.
4. Porta-Sanchez, R. Casado, O. Salvador, C. Sanchez-Enrique, S. Bayona-Horta, P. Sanchez-Borque, J. R. Campal, and J. A. Cabrera, "Arritmias cardiacas," Med.-Programa de Formacion Medica Continuada Acreditado, vol. 13, no. 44, pp. 2568–2576, 2021, doi: 10.1016/j.med.2021.10.011.
5. S. M. P. Dinakarrao, A. Jantsch, and M. Shafique, "Computer-aided arrhythmia diagnosis with bio-signal processing," ACM Comput. Surv., vol. 52, no. 2, pp. 1–37, Mar. 2020, doi: 10.1145/3297711.
6. H. V. Huikuri, A. Castellanos, and R. J. Myerburg, "Sudden death due to cardiac arrhythmias," New England J. Med., vol. 345, no. 20, pp. 1473–1482, 2001.
7. B. Chen, Y. Guo, Y. Chen, H. Zheng, and T. Liu, "ECG classification based on unfixed-length segmentation of heartbeat," in Proc. IEEE Int. Conf. Consum. Electron., May 2019, pp. 1–2.
8. Z. Zhang, J. Dong, X. Luo, K.-S. Choi, and X. Wu, "Heartbeat classification using disease-specific feature selection," Comput. Biol. Med., vol. 46, pp. 79–89, Mar. 2014.
9. J. L. Fleg and H. L. Kennedy, "Cardiac arrhythmias in a healthy elderly population," Chest, vol. 81, no. 3, pp. 302–307, Mar. 1982.
10. T. A. Manolio, C. D. Furberg, P. M. Rautaharju, D. Siscovick, A. B. Newman, N. O. Borhani, J. M. Gardin, and B. Tabatznik, "Cardiac arrhythmias on 24-h ambulatory electrocardiography in older women and men: The cardiovascular health study," J. Amer. College Cardiol., vol. 23, no. 4, pp. 916–925, Mar. 1994.
11. C.-M. Liu, S.-L. Chang, Y.-H. Yeh, F.-P. Chung, Y.-F. Hu, C.-C. Chou, K.-C. Hung, P.-C. Chang, J.-N. Liao, Y.-H. Chan, L.-W. Lo, L.-S. Wu, Y.-J. Lin, M.-S. Wen, and S.-A. Chen, "Enhanced detection of cardiac arrhythmias utilizing 14-day continuous ECG patch monitoring," Int. J. Cardiol., vol. 332, pp. 78–84, Jun. 2021.
12. X. Hua, J. Han, C. Zhao, H. Tang, Z. He, Q. Chen, S. Tang, J. Tang, and W. Zhou, "A novel method for ECG signal classification via onedimensional convolutional neural network," Multimedia Syst., vol. 28, no. 4, pp. 1387–1399, Aug. 2022.
13. D. Zhang, Y. Chen, Y. Chen, S. Ye, W. Cai, and M. Chen, "An ECG heartbeat classification method based on deep convolutional neural network," J. Healthcare Eng., vol. 2021, pp. 1–9, Sep. 2021.
14. F. Bouaziz and D. Boutana, "Automated ECG heartbeat classification by combining a multilayer perceptron neural network with enhanced particle swarm optimization algorithm," Res. Biomed. Eng., vol. 35, no. 2, pp. 143–155, Jun. 2019.
15. P. R. Jeyaraj and E. R. S. Nadar, "Computer-assisted medical image classification for early diagnosis of oral cancer employing deep learning algorithm," J. Cancer Res. Clin. Oncol., vol. 145, no. 4, pp. 829–837, Apr. 2019.
16. B. Liu, W. Chi, X. Li, P. Li, W. Liang, H. Liu, W. Wang, and J. He, "Evolving the pulmonary nodules diagnosis from classical approaches to deep learning-aided decision support: Three decades development course and future prospect," J. Cancer Res. Clin. Oncol., vol. 146, no. 1, pp. 153–185, Jan. 2020.
17. H. Khachnaoui, R. Guetari, and N. Khlifa, "A review on deep learning in thyroid ultrasound computer-assisted diagnosis systems," in Proc. IEEE Int. Conf. Image Process., Appl. Syst. (IPAS), Dec. 2018, pp. 291–297, doi: 10.1109/IPAS.2018.8708866.
18. MIT-BIH Arrhythmia Database. Accessed: Feb. 1, 2023. [Online]. Available: https://archive.physionet.org/physiobank/database/mitdb/
19. L. Goldberger, L. A. N. Amaral, L. Glass, J. M. Hausdorff, P. C. Ivanov, R. G. Mark, J. E. Mietus, G. B. Moody, C.-K. Peng, and H. E. Stanley, "PhysioBank, PhysioToolkit, and PhysioNet: Components of a new research resource for complex physiologic signals," Circulation, vol. 101, no. 23, pp. 215–220, Jun. 2000.
20. G. B. Moody and R. G. Mark, "The impact of the MIT-BIH arrhythmia database," IEEE Eng. Med. Biol. Mag., vol. 20, no. 3, pp. 45–50, May/Jun. 2001, doi: 10.1109/51.932724.
21. Z. F. M. Apandi, R. Ikeura, and S. Hayakawa, "Arrhythmia detection using MIT-BIH dataset: A review," in Proc. Int. Conf. Comput. Approach Smart Syst. Design Appl. (ICASSDA), Aug. 2018, pp. 1–5, doi: 10.1109/ICASSDA.2018.8477620.
22. K. Minami, H. Nakajima, and T. Toyoshima, "Real-time discrimination of ventricular tachyarrhythmia with Fourier-transform neural network," IEEE Trans. Biomed. Eng., vol. 46, no. 2, pp. 179–185, Feb. 1999, doi: 10.1109/10.740880.

DOI: 10.5123/inj.2023.4.in84
ISSN:2093-4777 | E-ISSN:2093-6931
Vol. 27 Iss. 4 (2023)

23. P. De Chazal, M. O'Dwyer, and R. B. Reilly, "Automatic classification of heartbeats using ECG morphology and heartbeat interval features," IEEE Trans. Biomed. Eng., vol. 51, no. 7, pp. 1196–1206, Jul. 2004.
24. P.-C. Chang, J.-J. Lin, J.-C. Hsieh, and J. Weng, "Myocardial infarction classification with multi-lead ECG using hidden Markov models and Gaussian mixture models," Appl. Soft Comput., vol. 12, no. 10, pp. 3165–3175, Oct. 2012.
25. S. Pan, T. Hong, and H. Chen, "ECG signal analysis by using hidden Markov model," in Proc. Int. Conf. Fuzzy Theory Appl. (iFUZZY), Nov. 2012, pp. 288–293, doi: 10.1109/iFUZZY.2012.6409718.
26. K. N. Rajesh and R. Dhuli, "Classification of ECG heartbeats using nonlinear decomposition methods and support vector machine," Comput. Biol. Med., vol. 87, pp. 271–284, Aug. 2017.
27. L. V. R. Kumari and Y. P. Sai, "Classification of arrhythmia beats using optimized k-nearest neighbor classifier," Intell. Syst., vol. 185, pp. 349–359, Apr. 2021.
28. Y. Toulni, T. B. Drissi, and B. Nsiri, "ECG signal diagnosis using discrete wavelet transform and K-nearest neighbor classifier," in Proc. 4th Int. Conf. Netw., Inf. Syst. Acad. Manag. Perspect. Security., Apr. 2021, pp. 1–6.
29. M. Kropf, D. Hayn, and G. Schreier, "ECG classification based on time and frequency domain features using random forests," in Proc. Comput. Cardiology (CinC), Sep. 2017, pp. 1–4, doi: 10.22489/CinC.2017.168- 168.
30. W. Zhu, X. Chen, Y. Wang, and L. Wang, "Arrhythmia recognition and classification using ECG morphology and segment feature analysis," IEEE/ACM Trans. Comput. Biol. Bioinf., vol. 16, no. 1, pp. 131–138, Jan. 2019, doi: 10.1109/TCBB.2018.2846611.
31. Mincholé, J. Camps, A. Lyon, and B. Rodríguez, "Machine learning in the electrocardiogram," J. Electrocardiol., vol. 57, pp. 61–64, Nov. 2019.
32. Goodfellow, Y. Bengio, and A. Courville, Deep Learning. Cambridge, MA, USA: MIT Press, 2017.
33. S. Hong, Y. Zhou, J. Shang, C. Xiao, and J. Sun, "Opportunities and challenges of deep learning methods for electrocardiogram data: A systematic review," Comput. Biol. Med., vol. 122, Jul. 2020, Art. no. 103801.
34. F. Murat, O. Yildirim, M. Talo, U. B. Baloglu, Y. Demir, and U. R. Acharya, "Application of deep learning techniques for heartbeats detection using ECG signals-analysis and review," Comput. Biol. Med., vol. 120, May 2020, Art. no. 103726.
35. Z. Ebrahimi, M. Loni, M. Daneshtalab, and A. Gharehbaghi, "A review on deep learning methods for ECG arrhythmia classification," Exp. Syst. Appl., X, vol. 7, Sep. 2020, Art. no. 100033.
36. G. Kumar, U. Pawar, and R. O'Reilly, "Arrhythmia detection in ECG signals using a multilayer perceptron network," in Proc. AICS, 2019, pp. 353–364.
37. P. H. Borghi, R. C. Borges, and J. P. Teixeira, "Atrial fibrillation classification based on MLP networks by extracting jitter and shimmer parameters," Proc. Comput. Sci., vol. 181, pp. 931–939, Jan. 2021.
38. S. Singh, S. K. Pandey, U. Pawar, and R. R. Janghel, "Classification of ECG arrhythmia using recurrent neural networks," Proc. Comput. Sci., vol. 132, pp. 1290–1297, Jan. 2018.
39. E. S. Simanjuntak, M. L. Khodra, and M. C. T. Manullang, "Design methods of detecting atrial fibrillation using the recurrent neural network algorithm on the Arduino AD8232 ECG module," IOP Conf. Ser., Earth Environ. Sci., vol. 537, no. 1, Jul. 2020, Art. no. 012022.
40. Gao, H. Zhang, P. Lu, and Z. Wang, "An effective LSTM recurrent network to detect arrhythmia on imbalanced ECG dataset," J. Healthcare Eng., vol. 2019, pp. 1–10, Oct. 2019.
41. B.-H. Kim and J.-Y. Pyun, "ECG identification for personal authentication using LSTM-based deep recurrent neural networks," Sensors, vol. 20, no. 11, p. 3069, May 2020.
42. J. Wang, "An intelligent computer-aided approach for atrial fibrillation and atrial flutter signals classification using modified bidirectional LSTM network," Inf. Sci., vol. 574, pp. 320–332, Oct. 2021.
43. R. Rohmantri and N. Surantha, "Arrhythmia classification using 2D convolutional neural network," Int. J. Adv. Comput. Sci. Appl., vol. 11, no. 4, pp. 201–208, 2020.
44. J. Ferretti, V. Randazzo, G. Cirrincione, and E. Pasero, "1-D convolutional neural network for ECG arrhythmia classification," in Progresses in Artificial Intelligence and Neural Systems. Singapore: Springer, 2020, pp. 269–279.
45. H. Wang, H. Shi, X. Chen, L. Zhao, Y. Huang, and C. Liu, "An improved convolutional neural network based approach for automated heartbeat classification," J. Med. Syst., vol. 44, no. 2, Feb. 2020.
46. B. M. Mathunjwa, Y.-T. Lin, C.-H. Lin, M. F. Abbod, and J.-S. Shieh, "ECG arrhythmia classification by using a recurrence plot and convolutional neural network," Biomed. Signal Process. Control, vol. 64, Feb. 2021, Art. no. 102262.

47. H. M. Rai and K. Chatterjee, "Hybrid CNN-LSTM deep learning model and ensemble technique for automatic detection of myocardial infarction using big ECG data," Int. J. Speech Technol., vol. 52, no. 5, pp. 5366–5384, Mar. 2022.
48. G. Petmezas, K. Haris, L. Stefanopoulos, V. Kilintzis, A. Tzavelis, J. A. Rogers, A. K. Katsaggelos, and N. Maglaveras, "Automated atrial fibrillation detection using a hybrid CNN-LSTM network on imbalanced ECG datasets," Biomed. Signal Process. Control, vol. 63, Jan. 2021, Art. no. 102194.
49. N. Lopac, F. Hržic, I. P. Vuksanovic, and J. Lerga, "Detection of non-stationary GW signals in high noise from Cohen's class of timefrequency representations using deep learning," IEEE Access, vol. 10, pp. 2408–2428, 2022.
50. E. H. Houssein, D. S. Abdelminaam, I. E. Ibrahim, M. Hassaballah, and Y. M. Wazery, "A hybrid heartbeats classification approach based on marine predators algorithm and convolution neural networks," IEEE Access, vol. 9, pp. 86194–86206, 2021, doi: 10.1109/ACCESS.2021.3088783.
51. D. K. Atal and M. Singh, "Arrhythmia classification with ECG signals based on the optimization-enabled deep convolutional neural network," Comput. Methods Programs Biomed., vol. 196, Nov. 2020, Art. no. 105607.
52. F. Bouaziz, H. Oulhadj, D. Boutana, and P. Siarry, "Automatic ECG arrhythmias classification scheme based on the conjoint use of the multi-layer perceptron neural network and a new improved metaheuristic approach," IET Signal Process., vol. 13, no. 8, pp. 726–735, Oct. 2019.
53. Nainwal, Y. Kumar, and B. Jha, "An ECG classification using DNN classifier with modified pigeon inspired optimizer," Multimedia Tools Appl., vol. 81, no. 7, pp. 9131–9150, Mar. 2022.
54. A. Abdelhamid, E. M. El-Kenawy, B. Alotaibi, G. M. Amer, M. Y. Abdelkader, A. Ibrahim, and M. M. Eid, "Robust speech emotion recognition using CNN+LSTM based on stochastic fractal search optimization algorithm," IEEE Access, vol. 10, pp. 49265–49284, 2022, doi: 10.1109/ACCESS.2022.3172954.
55. P. Sharma, S. K. Dinkar, and D. V. Gupta, "A novel hybrid deep learning method with cuckoo search algorithm for classification of arrhythmia disease using ECG signals," Neural Comput. Appl., vol. 33, no. 19, pp. 13123–13143, Oct. 2021.
56. P. Madan, V. Singh, D. P. Singh, M. Diwakar, B. Pant, and A. Kishor, "A hybrid deep learning approach for ECG-based arrhythmia classification," Bioengineering, vol. 9, no. 4, p. 152, Apr. 2022, doi: 10.3390/bioengineering9040152.
57. E. H. Houssein, A. A. Ewees, and M. A. ElAziz, "Improving twin support vector machine based on hybrid swarm optimizer for heartbeat classification," Pattern Recognit. Image Anal., vol. 28, no. 2, pp. 243–253, Apr. 2018.
58. Navaneeth and M. Suchetha, "PSO optimized 1-D CNN-SVM architecture for real-time detection and classification applications," Comput. Biol. Med., vol. 108, pp. 85–92, May 2019.
59. E. H. Houssein, D. S. Abdelminaam, H. N. Hassan, M. M. Al-Sayed, and E. Nabil, "A hybrid barnacles mating optimizer algorithm with support vector machines for gene selection of microarray cancer classification," IEEE Access, vol. 9, pp. 64895–64905, 2021, doi: 10.1109/ACCESS.2021.3075942.
60. E. J. D. S. Luz, W. R. Schwartz, G. Cámara-Chávez, and D. Menotti, "ECG-based heartbeat classification for arrhythmia detection: A survey," Comput. Methods Programs Biomed., vol. 127, pp. 144–164, Apr. 2016.
61. U. R. Acharya, H. Fujita, M. Adam, O. S. Lih, V. K. Sudarshan, T. J. Hong, J. E. Koh, Y. Hagiwara, C. K. Chua, C. K. Poo, and T. R. San, "Automated characterization and classification of coronary artery disease and myocardial infarction by decomposition of ECG signals: A comparative study," Inf. Sci., vol. 377, pp. 17–29, Jan. 2017.
62. G. B. Moody and R. G. Mark, "The MIT-BIH arrhythmia database on CD-ROM and software for use with it," in Proc. Comput. Cardiology, Sep. 1990, pp. 185–188, doi: 10.1109/CIC.1990.144205.
63. Kachuee, S. Fazeli, and M. Sarrafzadeh, "ECG heartbeat classification: A deep transferable representation," in Proc. IEEE Int. Conf. Healthcare Informat. (ICHI), Jun. 2018, pp. 443–444, doi: 10.1109/ICHI.2018.00092.
64. S. Albawi, T. A. Mohammed, and S. Al-Zawi, "Understanding of a convolutional neural network," in Proc. Int. Conf. Eng. Technol. (ICET), Aug. 2017, pp. 1–6, doi: 10.1109/ICEngTechnol.2017.8308186.
65. Q. Zhang, "Convolutional neural networks," in Proc. 3rd Int. Conf. Electromechanical Control Technol. Transp., 2018, pp. 434–439.
66. V. Thakkar, S. Tewary, and C. Chakraborty, "Batch normalization in convolutional neural networks—A comparative study with CIFAR-10 data," in Proc. 5th Int. Conf. Emerg. Appl. Inf. Technol. (EAIT), Jan. 2018, pp. 1–5, doi: 10.1109/EAIT.2018.8470438.
67. J. Kennedy and R. Eberhart, "Particle swarm optimization," in Proc. Int. Conf. Neural Netw., 1995, pp. 1942–1948, doi: 10.1109/ICNN.1995.488968.

68. F. E. F. Junior and G. G. Yen, "Particle swarm optimization of deep neural networks architectures for image classification," Swarm Evol. Comput., vol. 49, pp. 62–74, Sep. 2019.
69. T. M. Shami, A. A. El-Saleh, M. Alswaitti, Q. Al-Tashi, M. A. Summakieh, and S. Mirjalili, "Particle swarm optimization: A comprehensive survey," IEEE Access, vol. 10, pp. 10031–10061, 2022, doi: 10.1109/ACCESS.2022.3142859.
70. Lopac, I. Jurdana, J. Lerga, and N. Wakabayashi, "Particle-swarm optimization-enhanced radial-basis-function-kernel-based adaptive filtering applied to maritime data," J. Mar. Sci. Eng., vol. 9, no. 4, p. 439, Apr. 2021, doi: 10.3390/jmse9040439.
71. https://medium.com/@ottaviocalzone/an-intuitive-explanation-of-lstm-a035eb6ab42c
72. Ullah A, Anwar SM, Bilal M, Mehmood RM. Classification of Arrhythmia by Using Deep Learning with 2-D ECG Spectral Image Representation. Remote Sensing. 2020; 12(10):1685.
73. Farag, M.M. A Tiny Matched Filter-Based CNN for Inter-Patient ECG Classification and Arrhythmia Detection at the Edge. Sensors 2023, 23, 1365
74. Hassan SU, Mohd Zahid MS, Abdullah TA, Husain K. Classification of cardiac arrhythmia using a convolutional neural network and bi-directional long short-term memory. DIGITAL HEALTH. 2022;8. doi:10.1177/20552076221102766.
75. M. Bukhari, S. Yasmin, S. Naz, M. Y. Durrani, M. Javaid et al., "A smart heart disease diagnostic system using deep vanilla lstm," Computers, Materials & Continua, vol. 77, no.1, pp. 1251–1279, 2023.
76. Fredy Santander Baños, Norberto Hernández Romero, Juan Carlos Seck Tuoh Mora, Joselito Medina Marín et al. "A Novel Hybrid Model Based on Convolutional Neural Network with Particle Swarm Optimization Algorithm for Classification of Cardiac Arrhytmias", IEEE Access, 2023.
77. Anu Honnashamaiah & Dr. Rathnakara S., "Detection of Arrhythmia in ECG signal using Deep Learning Methods – A exhaustive review & summary of the concepts & techniques", Tuijin Jishu / Journal of Propulsion Technology, ISSN: 1001-4055, Indexed by Elsevier Scopus, SCI Q3, SJR 2022 – 0.32, SNIP 2022 1.069, H-Index 24, CiteScore 2022 1.1, DOI : 10.52783/tjjpt.v44.i4.1845, Vol. 44, Issue 4, pp. 5088-5095, Oct-Dec. 2023.
78. Anu Honnashamaiah & Dr. Rathnakara S., "ECG signal classification using CNN & LSTM with Aquila Optimization technique", Tuijin Jishu / Journal of Propulsion Technology, ISSN: 1001-4055, Indexed by Elsevier Scopus, SCI Q3, SJR 2022 – 0.32, SNIP 2022 1.069, H-Index 24, CiteScore 2022 1.1, DOI : 10.52783/tjjpt.v44.i4.1830, Vol. 44, Issue 4, pp. 5075 – 5087, Oct-Dec. 2023.