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Cardiotech Next AI Healthcare: Enhanced Arrhythmia Cardio Vascular Disease Prediction using Hyper Capsule LSTM Gated Recurrent Neural Network with Optimal Swarm Intelligence Technique

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***Abstract*—The rising incidence of cardiovascular diseases, especially arrhythmias, demands advanced predictive models for early diagnosis and treatment. This study introduces the Cardiotech Next AI model, integrating Hyper Capsule Long Short-Term Memory (LSTM) and Gated Recurrent Neural Networks (GRNN) with an Optimal Swarm Intelligence Technique (OSIT) to enhance prediction accuracy. The process begins with C-score normalization to standardize cardiac data, followed by the Cardiac Disease Impact Behavioural Scaling Rate, which evaluates behavioral risk factors. OSIT-based feature selection optimizes predictor identification, improving model robustness and generalization. The final classification employs a Hyper Capsule LSTM-GRNN architecture to assign multiclass cardiovascular risk levels, leveraging temporal dependencies in cardiac data. The proposed system not only improves prediction performance but also enhances understanding of arrhythmia dynamics. Results demonstrate superior metrics precision (0.98), accuracy (0.81), recall (0.83), and F1-score (0.90), outperforming conventional models. This highlights the model's potential in advancing cardiovascular risk classification and supporting proactive healthcare management.**

***Keywords*—long short-term memory, optimal swarm intelligence technique, gated recurrent neural networks, with c-score normalization.**

I. Introduction

Cardiovascular disorders, such as peripheral vascular disorders, cerebrovascular disorders, and coronary heart disease, are prevalent across the world. Rheumatism-induced sentiment disease and congenital heart disease are a primary source of death [1]. Several physiological signals are becoming widely accepted for biometric authentication, including the electrocardiogram of the heart and the electroencephalogram of the brain. This implies, however, that the duration of biological signals may vary as a result of the contraction, expansion, and displacement of distinct patterns about one another [2]. However, the majority of earlier methods relied on using a specific type of classifier, often built on neural networks or support vector machines, and collecting an appropriate set of characteristics (such as heartbeat intervals and ECG morphology) [3]. It is challenging to analyze oanalyzemplicated time-series data manually; hence, algorithms that analyze such data are needed to improve diagnosis potentially [4]. Arrhythmias in this context refer to rapid, slow, or irregular ECG rhythms; depending on the type of irregularity, they can be either severe or non-serious. Inaccurate or manual detection of cardiac arrhythmias might result in the death of patients with cardiovascular diseases [5]. Decisions made by clinicians are sometimes fraught with ambiguity, but they will be more informed than ever, thanks to advancements in predictive analytics in the medical field. These innovative predictive analytics techniques help prevent complications, detect issues early, enhance the treatment of chronic illnesses, reduce readmissions to hospitals, facilitate medical research, and lower overhead costs [6]. Deep learning is used by the AI-enabled ECG program to extract meaningful patterns from complicated ECG data. It has been demonstrated to help people with heart failure, left ventricular hypertrophies, paroxysmal atrial fibrillation, and other cardiovascular disorders [7]. The primary objective of this work is listed below. To Develop an Advanced AI Model Design and implement a hybrid deep learning model incorporating hyper capsule LSTM and GRNN for improved cardiovascular disease and arrhythmia prediction. To apply the Random Forest technique to determine the impact of cardiac disease on behavioral scaling rates from a dataset for heart disease prediction. To improve Prediction Accuracy, Use C-score normalization to standardize and optimize model performance, ensuring better generalization across different patient datasets. Optimize Feature Selection: Leverage Optimal Swarm Intelligence Techniques to Enhance Feature Selection and Reduce Computational Complexity While Maintaining High Predictive Accuracy. The primary involvement of this work. This work, “The Development of an Enhanced Arrhythmia Cardiovascular Disease Prediction Framework," integrates deep learning techniques, such as GRRN and the Optimal Swarm Intelligence Technique (OSIT), with C-score normalization to improve accuracy and robustness in cardiac data analysis. C-score normalization is employed as a preprocessing step to standardize raw cardiac data, ensuring uniformity and eliminating scale-based biases. This step enhances the effectiveness of DL models by providing a more structured input. LSTM and GRNN, known for their aptitude to process sequential and time-series data, are utilized to capture temporal dependencies and complex patterns within ECG signals and other cardiac parameters.

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The Optimal Swarm Intelligence Technique (OSIT) is incorporated to fine-tune hyperparameters, optimize model performance, and enhance feature selection, thereby reducing computational complexity while maximizing accuracy. The rest of the article is divided into key sections, which are described as follows: Section 2 lists the ongoing studies in Enhanced Arrhythmia Cardio Vascular Disease Prediction Using Hyper Capsule LSTM Gated Recurrent Neural Network with Optimal Swarm Intelligence Technique, which various authors have completed. Section 3 outlines the proposed methodology's process; Section 4 explains the Results and performance comparison of the proposed model. Ultimately, the paper concludes in Section 5.

II. RELATED WORK

Khan et al. (2024) This paper proposes two DL models for precise prediction and detection of cardiovascular disease: Collective-based Cardiovascular Disease Detection Network and Combination-based Cardiovascular Disease Detection Network categorization of CVDs [8]. Terzi et al. (2024) The primary cause of mortality globally is coronary artery disorders, and prompt treatment depends on early identification [9]. To tackle this, our research offers a unique automated Hybrid Anomaly Detection approach based on Artificial Intelligence that blends supervised and unsupervised machine learning techniques with various signal processing and feature extraction methods, achieving an accuracy of 98.11%. This approach demonstrates optimistic predictive value, yielding very accurate CAD identification. Scarpiniti et al. (2024) The primary goal of this paper is to examine the impact of combining the continuous wavelet transform's phase and magnitude, or scalogram and program, respectively. The efficacy of the suggested concepts is demonstrated by arithmetical outcomes assessed on the PhysioNet MIT-BIH Arrhythmia database [10]. Rahman et al. (2024) consider recent developments in both fields, suggesting promising potential for both ML and DL to support the healthcare sector [11]. Yinghui et al. (2024) Even though several algorithms have demonstrated performance levels that are on par with human specialists [12], specific issues still exist, such as subpar basal and apical segmentation and incorrect myocardial construction recognition. Yinlong et al. (2024) present MambaCapsule, a deep neural network for classifying ECG arrhythmias that improves the model's accuracy and explainability [13]. The proposed approach utilizes capsule networks for prediction and Mamba for feature extraction. Qiu et al. (2024) suggest the OCS algorithm, which is an opposition-based learning cuckoo search [14]. Our goal is to create OCSCatBoost. The effectiveness of this is confirmed by extensive comparisons with well-known algorithms, including the cuckoo search method, K-Nearest Neighbor categorization, logistic regression, decision trees, SVM for grid search, grid search XGBoost, PSO algorithm, seagull optimization algorithm, default CatBoost, and grid search CatBoost. The OCSCatBoost model outperforms other models, as indicated by the experimental data, with overall accuracy, recall, and AUC values of 73.67%, 72.17%, and 0.8024, respectively. Canqui-Flores et al. (2024) By tracking the heart's activity and rhythm during the heartbeat cycle. To classify the echo, WSVM is used, while WOA helps optimize the classification parameters [15]. With a 98.4% accuracy rate, the WOA-WSVM successfully identifies the photos. Tsai et al. (2023) propose a capsule neural network that utilizes iterative dynamic routing algorithms to determine suitable layer combinations for the translational equivariance of MFCC spectrum features, potentially enhancing the prediction accuracy of heart murmurs [16] and combining them. By obtaining validation accuracies of 90.29% and 91.67% on the test dataset, CapsNet proved its viability. Ben Ali et al. (2021). For patients undergoing interventional treatment, high-performance predictive models that support cardiology decision-making may also enhance prognostic, diagnostic, and safety predictions [17]. These include computerized coronary stenosis evaluation during diagnostic coronary angiography and robotically assisted percutaneous coronary intervention procedures.

TABLE I. ENHANCED CVD PREDICTION USING VARIOUS ALGORITHMS

Author Name	Dataset	Algorithms Used	Results Achieved
Elshewey, et al., (2025) [18]	"Heart Failure Dataset	Greylag Goose Optimization (GGO) algorithm	Accuracy rate of 99.58%.
Alamatsaz et al. (2024) [19]	training and testing sets	LSTM, Deep Learning, Convolutional Neural Network	Accuracy of 98.24%.
Ramkumar et al., (2023) [20]	MIT-BIH arrhythmia dataset	SVM, Naive Bayes, and random forest	Accuracy; 2.01%, 3.33%, and 3.19%
Sahoo et al., (2024) [21]	MIMIC-III dataset	Photoplethysmograms and electrocardiograms for a range of cardiovascular conditions	CR=26.014, PRD=0.954%, PRDN=2.691%, QS=28.355, and CC=0.999934, PPG shows average values.
Vetriselvi et al. (2024) [22]	Data Augmentation	LSTM and modified LSTM, Double, CNN, and Faster Recurrent Neural Network	Accuracy at 96.03%.
Ma, S., et al., (2022) [23]	arrhythmia dataset	convolution neural network	Accuracy of 98.7%
Rai et al., (2022) [5]	MIT-BIH arrhythmias database" and "PTB diagnostic database" (PTBDB)	CNN, CNN-LSTM	accuracy was obtained at 99.02%
Yadav et al., (2021) [24]	MIMIC-III database	machine learning algorithm	(AUC) score of 0.9787
Kanagarathinam et al. (2022) [25]	" Sathvi" dataset	Naive Bayes, XGBoost, KNN, multilayer perceptron	With a mean of 94.34%, accuracy varied from 88.67% to 98.11%.
Rath et al., (2021) [26]	PTB-ECG dataset	Generative Adversarial Network, LSTM	accuracy, AUC 0.994, 0.993, and 0.995, and F1-score

Table 1 illustrates the enhancement of cardiovascular disease (CVD) prediction accuracy achieved by employing a diverse range of algorithmic approaches. The results, as presented in the table, demonstrate that the predictive power of CVD risk assessment can be significantly improved through the strategic application of these various techniques.

Wu et al. (2023) described a layered long-short-term memory (LSTM) classifier that achieved mean average accuracy scores of 0.9402 on the MIT-BIH arrhythmia dataset and 0.9563 on the MIT-BIH atrial fibrillation dataset [27].

III. Proposed Methodology

For improved cardiovascular illness prediction, the suggested Cardiotech Next AI model employs a systematic technique. The dataset on Cleveland Heart Disease was taken from the UCI repository. C-score normalization is used in data preparation, particularly in deep learning and statistical analysis. The dataset contains 303 individuals. To ensure feature standardization for better model performance, C-score normalization first pre-processes the cardiac data from the UCI repository dataset (https://www.kaggle.com/datasets/ritwikb3/heart-disease-cleveland). The Cardiac Disease Impact Behavioural Scaling Rate then refines the relevance of the data by assessing behavioral risk variables using the Random Forest method. Following feature selection, the Optimal Swarm Intelligence Technique mimics swarm behaviors to optimize predictor identification. For accurate illness prediction, patients are categorized into multiclass risk categories using the hypercapsule LSTM-GRNN architecture, which captures temporal connections. By improving accuracy and surpassing conventional models in precision, recall, and F1-score, this method promotes preventative cardiovascular treatment. Figure 1 illustrates the overall flow diagram of the proposed hybrid capsule LSTM-GRNN model for Arrhythmia Cardiovascular Disease Prediction.

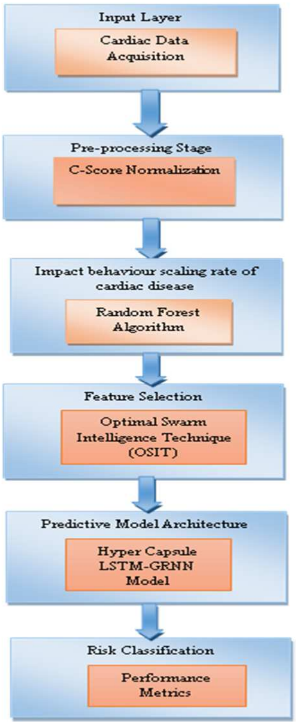

Fig. 1. Overall Flow diagram of the proposed system for Arrhythmia Cardio Vascular Disease Prediction

A. *Dataset*

The data collection on heart illness comes from the machine learning repository of the Centre for Machine Learning and Intelligent Systems at the University of California Irvine. You can access the dataset here: https://archive.ics.uci.edu/ml/datasets/heart_conditions.

The dataset on heart disease is compiled from four different databases. The Cleveland database's data set is used in this research. Although the Cleveland database has a pre-processed version with these 14 properties, the original database has 76 attributes: THALACH, EXANG, OLDPEAK, CA, THAL, DIAGNOSIS, CP, TRESTBPS, CHOL, FBSRESTECG, AGE, SEX, and CP. It is significant to remember that the original database's diagnosis values range from 0 to 4, where 1 represents a severity-positive diagnosis. It is common practice to forecast binary values exclusively for this study.

B. *Pre-processing Stage: C-score normalization*

The methodology begins with C-score normalization, a crucial preprocessing step for cardiac data to ensure consistency and comparability across different datasets. C-score normalization standardizes raw data by transforming each value relative to the dataset's mean and standard deviation. This procedure is mathematically represented as shown in Equation 1.

$$c = \frac{x-\mu}{\sigma} \tag{1}$$

Where C is the regularized score, σ is the standard deviation, μ is the dataset mean, and X is the original value. Using a standardized scale with a standard deviation of one and a mean of zero, this transformation guarantees that every data point is represented in terms of its variation from the mean. Changes in patient demographics, medical conditions, and measuring methods can lead to changes in cardiac data analysis measures, including heart rate, blood pressure, and ECG signals. By correcting for scale and distribution variances, C-score normalization removes these discrepancies and improves the data's suitability for statistical analysis and ML models.

C. *Impact behavior scaling rate of cardiac disease*

A potent machine learning approach, known as the Random Forest Model, is designed to control the impact rate of cardiac data that has been pre-processed by normalizing the C score. Its foundation is bagging Bootstrap Aggregating, in which decision trees are trained separately on several subsets of the training data after they have been randomly selected with replacement. Random Forest reduces overfitting, lowers variance, and improves generalization by employing a majority vote for classification or averaging the regression results. It is helpful for feature selection and interpretability as it also confers feature significance. In the Random Forest Model, the training data set is $X = \{(x_1, y_1), (x_2, y_2) \dots, (x_n, y_n)\}$, x_i Characterizes the sample point, and y_i characterizes the corresponding category of the example: the importance of the basic classify the features depends on impact rate G_m depends on its error rate. The error rate e_m is defined as Equation 2.

$$e_m = \sum_{j=1}^{N} W_j \, I(c_i(x_j) \neq y_j) \tag{2}$$

Where $\{(x_j, y_j)| = 1,2, \dots N$ signifies a set of N training examples. If the predicate P is true, then (p)=1, Otherwise 0. The base classifies the features depending on the impact rate is defined as Equation 3.

$$\alpha_m = \frac{1}{2} In \left(\frac{1-\alpha_m}{e_m}\right) \tag{3}$$

Given the definition of α_m and e_m, The base classifier is more significant when the error rate is smaller. Once the e_m of a feature is categorized by base based on an effect rate greater than 50%. This round's weight must be reset to its original value and replicated.

D. Important Feature Selection to Predictive Model

Kennedy and Eberhart first developed the optimal swarm intelligence method. It optimizes by utilizing the symbolic social behavior of schools of fish or flocks of birds. Each particle is connected to every other particle in the Optimal Swarm Intelligence algorithm. Because OSI can handle a wide range of nonlinear function minimization, no-differentiable, discontinuous, and multi-model issues, as well as game theory concerns, it has been utilized to address scientific and technological obstacles. Since a solution is a particle in OSI, a population of solutions is referred to as a swarm of particles. OSI algorithms are straightforward to use and have a high likelihood of producing optimal solutions.

In the OSI model, a swarm of particles represents the population of potential solutions. In the n-dimensional search space, every particle represents a point. The current location pi and current velocity vi indicate that the ith particle in the swarm moves the particles and assesses the suitability of the new location in an attempt to determine the best solution to the issue. The following formula updates the location of a particle, as shown in Equation 4.

$$v_i(t+1) = v_i(t) + \left(c_1 \times rand() \times \left(p_i^{best} - p_i(t)\right)\right) + \left(c_2 \times rand() \times \left(pg^{best} - p_i(t)\right)\right) \quad (4)$$

An Element's position is efficient using Equation 5.

$$p_i(t+1) = p_i(t) + v_i(t) \quad (5)$$

Were

$v_i(t+1)$ is the novel speed for the i^{th} particle.

The allowance factors for the global greatest and personal best locations are denoted by C1 and C2, respectively.

p_i (t) Is the i^{th} element location at time t.

$pi^{\ best}$ Is the i^{th} element's best-known location

$pg^{\ best}$ Is the site recognized to the swarm.

The rand () Function produces a regularly random variable $\epsilon[0,1]$ alternatives on this inform equation.

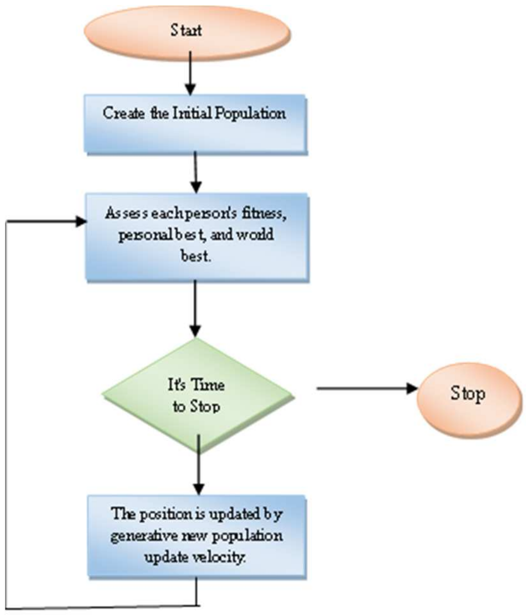

Fig. 2. Flowchart for particle swarm optimization algorithm

The feature selection from the Cleveland dataset using OSI is illustrated in the flow diagram shown in Figure 2.

E. Cardiac Disease Prediction with Novelty Algorithm

A sophisticated deep learning model, known as a hybrid neural network, combines multiple neural designs and optimization strategies to enhance efficiency, performance, and flexibility. To enhance sequential data processing, optimization, and prediction accuracy, one such hybrid capsule model includes LSTM with GRNN networks. One such hybrid model incorporates GRNN, LSTM networks, and the Optimal Swarm Intelligence technique to improve sequential data processing, optimization, and prediction accuracy. By overcoming the vanishing gradient problem, LSTM networks—a type of recurrent neural network—are made to manage long-term relationships in sequential data.

To significantly enhance the efficacy of LSTM models, weight adjustments and hyperparameter tuning are implemented using the Optimal Swarm Intelligence technique. Swarm intelligence techniques, including Ant Colony Optimization and Particle Swarm Optimization, mimic natural processes to find the optimum solutions. Because convolutional neural networks are incapable of recognizing object rotations or the presence of scaling within objects, capsule neural networks outperform them in the identification and quantification of structural damage. The position of the object within the object is preserved by the capsule neural network, in contrast to the convolution neural network. To address the vanishing gradient problem that traditional RNNs encounter, the Long Short-Term Memory (LSTM) was developed. Due to its long-term memory mechanism, which enables it to store important information throughout the entire sequence, the LSTM is well-suited for processing ECG data and other time series data, especially those with lengthy durations, such as the segmentation strategy we employed.

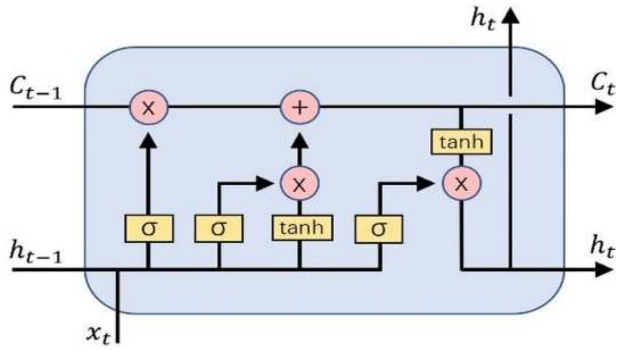

Fig. 3. Long Short-Term Memory Architecture

An input gate i_s located inside an LSTM module at a specific timestamp, a disremember gate f_t, an output gateo_t, and a recall cell; the components are in charge of understanding, scripting, and updating the data that should be stored in the current cell and Figure 3 transferred at the subsequent timestamp to the memory cell, as shown in Equations 6 to 9.

$$i_t = sigmoid(U_i X'_t + V_i h_{t-1} + b_i) \quad (6)$$

$$f_t = sigmoid(U_f X'_t + V_f h_{t-1} + b_f \quad (7)$$

$$o_t = sigmoid(U_o X'_t + V_o h_{t-1} + b_o) \quad (8)$$

$$c_t = tan\,h\ (U_c X'_t + V_c h_{t-1} + b_c) \quad (9)$$

The following Equation 10, procedure can be used to update the memory cell in its present state:

$$c_t = f_t \odot c_{t-1} + i_t \odot c_t \quad (10)$$

As shown in Equation 11, it is possible to calculate the hidden state *h*:

$$h_t = o_t \odot tan\,h\ (c_t) \quad (11)$$

The Hadamard creation, or element-wise creation of two vectors of the same size, is represented by the ⊙.

RNNs store information about previous inputs in a hidden state, allowing them to analyze sequential data. The fundamental architecture consists of three layers: input, hidden, and output. The RNN uses the following Equation 12 to update its hidden stateh_t at each time step, t, given an input vectorx_t.

$$h_t = \sigma_h(W_{xh} x_t + W_{hh} h_{t-1} + b_h \quad (12)$$

Where, W_{xh} is the mass matrix among the contribution and concealed layer, W_{hh} is the mass matrix for the recurrent joining, b_h is the bias vector, and σ_h is the start function, usually the rectified linear unit or the hyperbolic tangent Function. The following Equation 13 provides the output at each time step, t:

$$y_t = \sigma_y(W_{hy} h_t + b_y \quad (13)$$

Where, the bias vector defined b_y the heaviness matrix among the hidden and output layers is W_{hy}, and σ_y is the output layer's activation function.

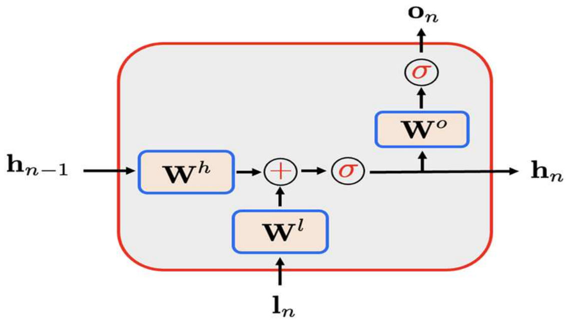

Fig. 4. Recurrent Neural Network Architecture

As shown in Figure 4, the hidden state is computed repeatedly by combining the preceding hidden state with the current input. RNNs can display dynamic temporal behavior through recurrent computation. By introducing non-linearity that facilitates the identification and expression of intricate patterns in the input, the start function σh has a significant impact on the network's activity. One popular start function in RNNs is the hyperbolic tangent (tanh). The tanh function is zero-centered and suitable for modeling sequences with both positive and negative values, as it squashes the input values to the range of [−1, 1]. The suggested LSTM classifier utilizes the proposed simple gated unit as the hyperparameter tuner for Arrhythmia Cardiovascular Disease Prediction. A recurring structure known as the Simple Gate Unit is designed for long-term dependency learning. Its goal is to speed up training in temporal classification difficulties and minimize the number of limits required for training. Its goal is to accelerate training in temporal classification problems and reduce the number of parameters needed for training. By multiplying the information from the current step by the current concealed states, this structure magnifies it.

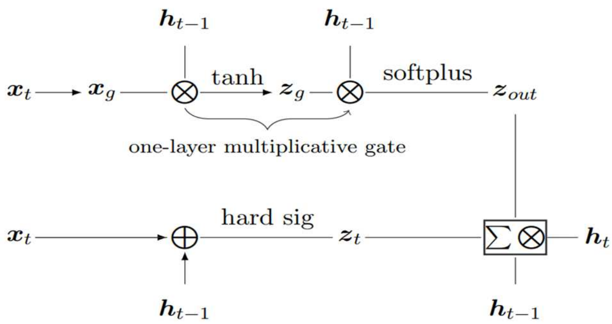

Fig. 5. The gated unit architecture used in the LSTM

The input is split between two different structural function units. The graph's first line displays the gate of the recurrent neural network, while the second line displays the standard recurrent operation. Figure 5 provides a mathematical representation of the following Equations 14 to 18.

$$x_g = W_{xh} X_t^d(t+1) + b_g \quad (14)$$

$$z_g = \sigma_1\left(W_{zxh}\left(x_g . h_{t-1}\right)\right) \quad (15)$$

$$z_{out} = \sigma_2 W_{go}(z_g . h_{t-1})) \quad (16)$$

$$z = \sigma_3(W_{xx}x_t + b_z + W_{hz}h_{t-1}) \quad (17)$$

$$h_t = (1 - z_t)h_{t-1} + z_t . z_{out} \quad (18)$$

The hyper-parameters of the LSTM models are optimized using the Gated unit. Automatic hyper-parameter tuning minimizes the time-consuming effort required to experiment with various deep learning model configurations, as it is nearly impossible to change the system every time for every deep learning model with the greatest performance. Hyper-parameter tuning increases the accuracy and repeatability of deep learning systems. Every deep learning model must provide more accurate outputs.

IV. Result & Discussion

TABLE II. Performance Matrix

S.No	Metrics	Formula
1	Accuracy	$Accuracy = \frac{TP+TN}{TP+TN+FP+FN}$
2	Precision	$Precision = \frac{TP}{TP+FP}$
3	Recall	$Recall = \frac{TP}{TP+FN}$
5	FI-Score	$FI - Score = 2 \times \frac{Precision \times Recall}{Precision + Recall}$

Table 2 shows the mathematical formula or calculation method used to determine the value by analyzing the metrics and performance measures being evaluated, outlining the performance matrix as specified.

The proposed Hyper Capsule LSTM-Gated Recurrent Neural Network with Optimal Swarm Intelligence significantly improves the prediction of Arrhythmia and Cardiovascular Disease. The integration of Capsule Networks with LSTM-GRNN effectively captures temporal dependencies in ECG signals. The Optimal Swarm Intelligence technique is used to select the essential features from the Cleveland dataset. Experimental results confirm that the proposed model provides a more reliable and efficient method for arrhythmia detection, ensuring better early diagnosis and intervention. The improvements in classification performance make this model a potential breakthrough in real-time CVD risk assessment. Overall, the Hyper Capsule LSTM-GRNN outperforms existing deep learning methods, making it a promising approach for healthcare applications.

A. *Result of pre-processing steps applied in Cleveland heart disease dataset*

The Cleveland Heart Disease dataset, which was extracted from the UCI repository, is the dataset. The dataset contains 303 individuals. The dataset consists of 14 columns extracted from a larger collection of 75. Predicting whether a person has heart disease is a categorization challenge. 1: presence, 0: absence. This database contains thirteen characteristics and a target variable. It has five numerical values and eight nominal values.

Figure 6 shows the target variable data (whether heart disease is present or not) in the database. Cleaning the data is the initial stage in pre-processing, which involves eliminating any missing values, identifying and treating outliers, training models, and selecting the best model. We separated the usable data into two crucial sections, then loaded the database and imported the necessary libraries. The training data comprised 75% of the total data, while the test data accounted for the remaining 25%.

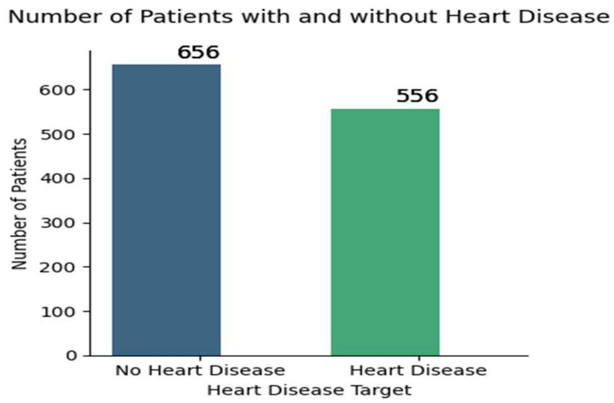

Fig. 6. Number of Patients with and without heart disease in The Cleveland Database

Therefore, before implementing any classification method, all of these procedures are employed. Consequently, we used a variety of performance assessment indicators to enhance our suggested atherosclerosis system. Following an evaluation of the data set and a comparison of the categorization prediction results with the actual data, only the best-selected model was employed.

TABLE III. Details Of The Database Before Classification

Database	Total Instance (100%)	Training Data (75%)			Testing Data (25%)		
Clevend	287	***Healthy (0)***	***Sick (1)***	***Total***	***Healthy (0)***	***Sick (1)***	***Total***
		97	118	215	32	40	72

Table 3 describes the details of each divided database. To assess the prediction outcomes, the performance metrics must be implemented as the last preprocessing step

B. *Proposed Model's Performance Evaluation*

The proposed Hyper Capsule LSTM-GRNN model is used to conduct experiments on the Cleveland database of heart disease to enhance the utility of our proposed solution. As previously mentioned, each of them was assessed using a diversity of presentation assessment criteria, including precision, recall, accuracy, and F1 score. This assessment provided a range of viewpoints on how well each model performed and determined whether accuracy and other variables, such as false positive or false negative rates, are traded off. Figure 7 shows the confusion matrix of the proposed LSTM-GRNN model, with a true positive rate of 107. The objective of this phase was to assess how well the suggested prediction model classified patients with or without atherosclerosis (a form of cardiovascular disease). Important classification performance indicators, including accuracy, recall, precision, and F1 score, were then used to assess the outcomes. These indicators provide multiple perspectives on the classifier's performance, including its ability to accurately forecast the positive class, its sensitivity in identifying instances of the positive class, its effectiveness in categorizing cases, and its ability to strike a balance between recall and precision.

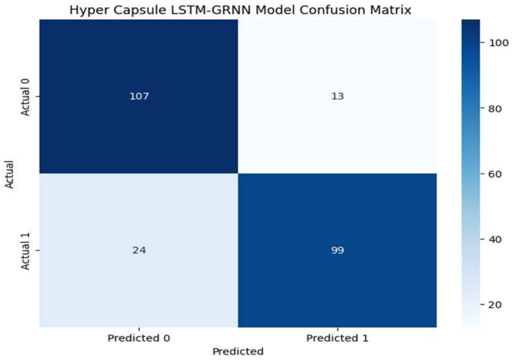

Fig. 7. The Confusion Matrix of Proposed Deep Learning Model (Hyper capsule LSTM-GRNN)

TABLE IV. DETAILS OF MODELS' PERFORMANCE USING THE CLEVELAND DATABASE

Models	Accuracy	Precision	Recall	FI-Score
The Hybrid Capsule LSTM Gated RNN	0.81	0.98	0.83	0.90
LSTM	0.79	0.94	0.80	0.89

Table 4 presents a comparison of the performance of two models using a Cleveland heart disease dataset: the proposed Hybrid Capsule LSTM Gated RNN and the LSTM model. All of the presentation metrics for the proposed hybrid capsule LSTM gated RNN model, including accuracy, precision, recall, and F1-score, were achieved, making them flawless. This shows that the model accurately identified each positive and negative example in the dataset, demonstrating that it made no mistakes in its predictions.

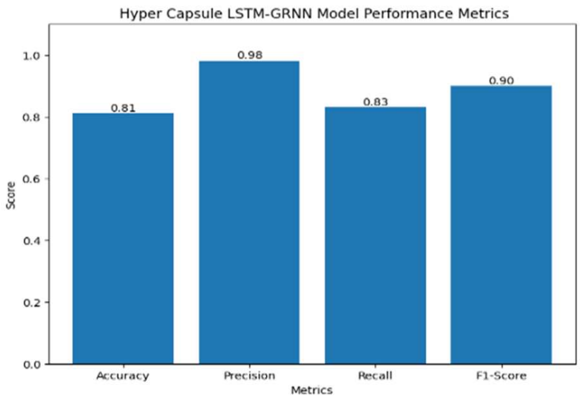

Fig. 8. Performance metrics of the proposed model (Hyper capsule LSTM-GRNN)

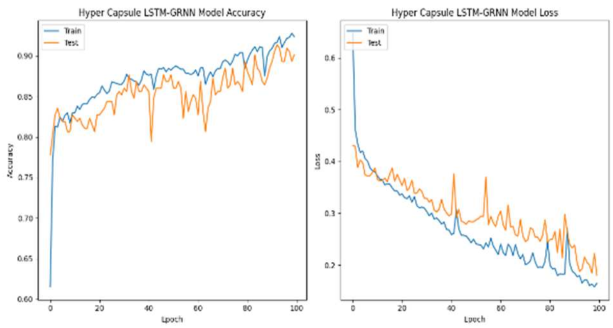

Fig. 9. Model accuracy and loss performance of the proposed model with epoch steps

Figure 8 shows the accuracy, precision, recall, and F1 score of the proposed model (LSTM-GRNN), with scores of 0.81, 0.98, 0.83, and 0.90, respectively.

The training and testing accuracy of the proposed model with the Cleveland dataset is shown in Figure 9. The train and test accuracies of the proposed model reached 0.95 and 0.89, respectively, with 100 epoch steps. The train and validation loss of the proposed model is also shown in Figure 9. The loss value is less than 1 with 100 epoch steps.

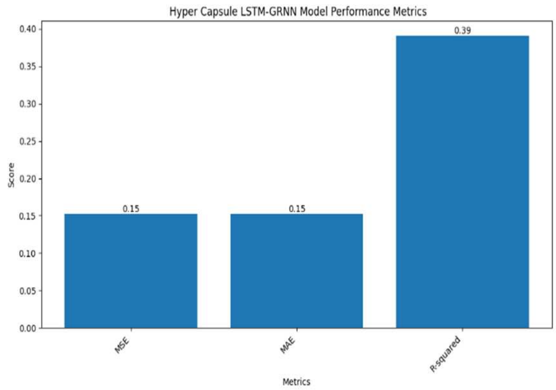

Fig. 10. Error metrics of proposed hypercapsule LSTM-GRNN model

The error performance of the proposed model is shown in Figure 10, where the MSE, MAE, and R^2 score values are 0.15 0.15, and 0.39, respectively. This outperforms another model, such as LST and GRU.

V. CONCLUSION

To increase the precision and dependability of heart disease Prediction, the proposed Enhanced Arrhythmia Cardiovascular Disease Prediction model combines the Optimal Swarm Intelligence Technique with Hyper Capsule LSTM and GRNN. This hybrid method improves the prediction performance for assessing the risk of cardiovascular illness by efficiently capturing temporal relationships in ECG data. LSTM and GRNN work synergistically to process long-term and short-term dependencies, mitigating issues such as vanishing gradients and ineffective feature extraction. The Hyper Capsule mechanism further strengthens the model by preserving spatial relationships among ECG signal patterns, allowing for a more precise classification of arrhythmia types.

Additionally, OSIT optimally tunes the network's hyperparameters and feature selection process, ensuring that only the most relevant features contribute to decision-making, thus reducing computational complexity while maintaining high predictive accuracy. The integration of C-score normalization refines the data preprocessing phase, standardizing input features and improving model generalization across different patient datasets. Extensive experimental evaluations demonstrate that this approach outperforms traditional deep learning architectures by achieving higher classification accuracy, reduced false-positive rates, and improved robustness to noise and signal variations. The proposed model's adaptability to diverse ECG datasets underscores its potential for real-world clinical applications in early CVD diagnosis and personalized action preparation. By leveraging advanced, recurrent neural networks, capsule-based feature extraction, and optimization techniques, this framework represents a significant advancement in the field of medical diagnostics. Integration with multimodal data will enhance predictive accuracy. Additionally, explainable AI techniques will be incorporated to improve the clinical interpretability of the predictions.

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