

α – DNN: OPTIMIZED-ATTENTION GUIDED DEEP NETWORK FOR PREDICTION OF CARDIAC ARREST

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ABSTRACT

The cardiologist can attend most cardiac arrests successfully by evaluating the various risk factors of patients. The ECG signals provide quantitative prognostics information with constant monitoring without considering random temporal information. This research model a novel Attention- Deep Neural Network model (α – DNN) with an optimization approach to capture the essential information for the earlier prediction of the neurological outcomes which causes sudden cardiac arrest. The proposed model includes three diverse phases: 1) Min-Max data normalization; b) Bounding-based weighted normalized feature learning; and c) prediction. Initially, the input is taken from the available online dataset for cardiac arrest. The dataset is verified for the minimal and maximal level of attribute range for a certain level. The bounding range of the data is provided with a weighted value for learning the features. The weighted function is multiplied with the dataset attribute values to measure the deviation level of the heart rate. The dynamic weighted function is optimized with stochastic Golden Eagle Optimizer (GEO) using Bellman Equation (BE). The optimal heart rate features are subjected to the Deep network model. This hybridized learning model is optimized with weights considering weights using an appropriate prediction algorithm. Furthermore, the proposed (α – DNN -GEO) comparative analysis is done with various existing approaches like Random Forest (RF), Decision tree (DT), Long Short-Term Memory (LSTM), Logistic Regression (LR) and hybrid approaches. Different performance metrics like sensitivity, specificity, PPV, NPV, and F1-score are evaluated and compared.

Keywords: *Cardiac Arrest; Deep Learning; Golden Eagle Optimizer; Deep Belief Network; Normalization*

1. INTRODUCTION

About 3.7% of patients encounter some unfavorable incidents like cardiopulmonary arrest, deaths without expectation and accidental ICU (Intensive Care Unit) admission during hospitalization [1]. The report provided by the United States and the Republic of Korea [2] specifies that the count of in-hospital cardiac arrests is increased [2]. Moreover, many studies often report abnormal vital signs that many minutes precede unfavorable actions [3]. The medical alert systems are used by the rapid response teams (RRTs) operated in many hospitals for quick response to these unfavorable incidents. The mortality is decreased, and it is evident that rates of the computational block, the input image represents as $x(t,0) = xt$, the customized computation block denotes $fres(.)$ that is the computational block from

non-ICU cardiac arrest are decreased by using the RRTs. Moreover, The RRTs' effects on rates of ICU transfer are ambiguous [4].

Many risk-scored models are required to find the patients, including inpatient death without expectation at high risk of important unfavorable incidents. VitalPACT™ Early Warning Score (ViEWS), Modified Early Warning Score (MEWS) and the National Early Warning Score (NEWS) [5] are the important early warning systems (EWSs) from more than 100 systems for identifying and managing the patients' clinical deterioration. Moreover, these systems provide low specificities and sensitivities [6].

the original design of ResNet which includes two stacks of three convolutional neural network units The association between cardiac arrest and

myocardial infarction (MI) is investigated by Gupta et al. [7] There are about 5869 cardiac arrest patients, 3122 (53.2%) patients who have coronary artery disease having no prior idea is found along with 1322 (42.3%), and 3122 patients have MI [8] without any symptoms. Particularly, about 67% of patients had abnormal electrocardiography (ECG) findings before cardiac arrests. The records have information about 46 cardiac arrest patients six years older than identified; about 21 (46%) had no arrhythmias [9]. The lab code data is related to deep and shallow learning [10]. A method is proposed for predicting cardiac arrest by analyzing bio signals measured via patch-type sensors in hospitalized patients. Deep learning and Machine learning are used in a few cases for predicting cardiac arrests. The cardiac arrest predictions for sensitivities are found by the MEWS, RF (Random Forest), and LR (Logistic Regression) as 0.3%, 23%, and 19.3% accordingly [11]. Machine Learning (ML) is used for the possible cardiac arrest prediction according to the development of big data. Electronic medical records (EMRs) are used for cardiac arrest scoring systems depending on the SVM (Support Vector Machines). The sex, age, vital signs, race, and lab data [12] are elements of the scoring system. The hematocrit, oximetry, heart rate, sodium, haemoglobin, systolic (SBP), diastolic (DBP), alkaline phosphatase, magnesium, glucose, temperature, total protein, creatinine, calcium, phosphate, carbon dioxide, albumin, platelet count, alanine aminotransferase, aspartate aminotransferase, and bilirubin are the lab data and vital signs.

The cardiac arrest model is used in ill patients critically presenting to the emergency department related to SVM within 72 hours. The sex, age, heart rate, medical history, respiratory rate, blood pressure, etiology, Glasgow coma scale, oxygen saturation, medication history, and heart rate variability (HRV) with time and frequency domain are the elements of the model [13]. The maximum heart rate, respiratory rate, minimum DBP, and pulse pressure index are found as the essential cardiac arrest predictors. A cardiac arrest risk triage (CART) scoring system with the help of temperature, time, heart rate, blood pressure, oxygen saturation, respiratory rate and mental status are developed. The evaluation of HRV and vital signs depend on the cardiac arrest model is performed by Support Vector Machine (SVM) within 72 hours [13]. The temperature, DBP, heart rate, SBP, Glasgow coma scale, pain score, oxygen saturation, and respiratory rate are included as the vital signs. The HRV is used to analyze the probabilistic neural network (PNN) and SVM. A DL-based early warning systems score

(DEWS) is developed [13]. There are four vital signs in DEWS score-based recurrent neural network (RNN) such as SBP, body temperature, heart rate, and respiratory rate [14]. An earlier cardiac prediction system is developed using ECG signal, heart rate, sex, body temperature, height, and age through the Internet of Things (IoT). The heart rate or abnormal body temperature is used to predict the system of cardiac arrest. The algorithms are developed for predicting cardiac arrest according to the RF in patients. The 8-hourly vital signs and the lab data are collected for two days to obtain the 24 hours of data [15]. The sensitivity is higher when only vital signs are used, yet lab data and vital signs provide the higher positive predictive value (PPV). The time-series data is used to investigate the predicted risk for clinical alerts depending on deep learning. The algorithms are developed for predicting the clinical risk depending on the shallow machine learning, and it is developed. The algorithms are developed to predict based on deep learning in healthcare with the help of multivariate time series data, and it is developed. ECG is used to validate the deep learning model. ECG is used to execute the shallow and deep learning algorithms. The deep learning-based algorithms are developed and validated to predict unfavorable incidents in the proposed system. The following are the major research contributions.

1) An online available cardiac arrest dataset is taken to monitor the ECG signals, and the systolic and diastolic frames are considered for analysis. The samples are normalized using Min-Max normalization, where the value ranges between 0 and 1.

2) The bounding box coordinates of the normalized data is taken and fed as a classifier input model known as attention-based Deep Neural Networks ($a - DNN$). The trained networks are considered for measuring the state of the systolic and diastolic rate, and the state action is measured using Bellman Equation (BE).

3) The weighted function of the network model is optimized using the novel Golden Eagle Optimizer (GEO), where the model intends to give global and local solutions. Thus, exploration and exploitation are achieved and fulfil the prediction requirements.

4) The simulation is done in MATLAB 2020a environment where diverse metrics like PPV, NPV, sensitivity, specificity and F1-score are evaluated and compared with diverse prevailing approaches.

The work is arranged as: Section 2 provides an extensive analysis on existing approaches, and the issues related to those models during cardiac arrest prediction are examined. In section 3, the research

methodology is elaborated, including prediction, classification and optimization. The numerical outcomes of the anticipated $a - DNN$ are discussed in section 4 with various statistical measures, followed by the conclusion in section 5.

2. RELATED WORKS

This section provides a detailed analysis of various existing approaches that helps to predict cardiac arrest. The shockable (SH) rhythm causes sudden cardiac arrest (SCA) that includes ventricular tachycardia (VT) and ventricular fibrillation (VF) to cause unexpected death from the outside environment of the clinic. The automated external defibrillator (AED) is used to treat the cardiac arrest ineffective way to identify the SH rhythms rapidly on ECG (Electrocardiogram) and provide the counter shock from the distorted electrical activity for recovering the general sinus heart rhythms [16]. Henceforth, the life-saving changes are improved by delivering the defibrillation with a short response time. AED is the most vital feature: the SAA (shock advice algorithm) to compile the performance requirement and the recommendations of the American Heart Association (AHA). It is important to note that the defibrillation is delivered from incorrect detection of non-shockable rhythms (NSH), which provides SP with 95% higher than the Se, which attains 90% by the rationale behind the recommendations AHA that generate the SCA artificially [17]. Moreover, the SAA performance is increased to pay the intensive attraction for reducing the incorrect diagnosis risks of the AED practically.

Most of the latest SAA designs in the study are used to enhance the performance accounted for on the schemes of conventional feature extraction (FE) [18]. It is achieved with the help of machine learning techniques (ML), stand-alone electrocardiogram (ECG), alternate signal or both of them for the classification purpose. Moreover, the classification models' performance depends remarkably on the input feature space quality extracted and the correlation among the individual in the complete combinations with the help of NSH signals and stand-alone ECG using the modified VMD (MVMD) [19]. Henceforth, the powerful representation and informative collection of input features for practically recognizing the SH rhythm is required [20]. The feature selection algorithms (FS) are adopted to accomplish and avoid the unwanted features to improve the machine learning classifier learning process from the input feature space [21].

Nonetheless, due to the knowledge of human

experts, which gains requirements, FS is a complex and time-consuming algorithm. However, the shockability oriented signal that is the SH signal is not examined concerned with enhancing the classification performance of NSH or SH rhythm. The CNN (convolutional neural networks) is used widely for design problems of application and biomedical signal processing. However, the CNN has eleven layers used to design the computer-aided diagnosis system for detecting atrial flutter, atrial fibrillation, and VF that are suggested. The same CNN structure is proposed to diagnose myocardial infarction [22]. However, the raw stand-alone ECG signal used for the 13 layers of CNN is considered the input for the detection of atrial fibrillation to generate better performance than the traditional features [23]. Particularly, deep neural networks (DNN) combine the deep learning features and the traditional features with the help of raw ECG, which is suggested as the ensemble XGBOOST classifier's input to diagnose atrial fibrillation [24]. The deep learning approach (DL) is adopted for the detection of SCA is suggested where the SAA is developed as the deep CNNs' eleven layers [25]. Generally, the CNNs' use behind rationale is the superior features like learning abilities of strong feature, low complexity due to the no need of traditional expertise-based FS and FE algorithms [26]. In addition, the ECG signal is used for the SAA design in the existing system [27] to pay importance to the particular structure of CNN that provides possible omitting structures of CNN effectively. Further, it is not considered the CNN learning features to train the independent machine learning classifier to enhance the SCA detection performance in the research of SAA design [28]. It is important to note that it is essential for examining the various input channels utilities like NSH signals and SH signals, stand-alone ECG segment than the stand-alone ECG segment to enhance the feature learning quality as the single input channel for the CNN [29] - [30]. This work intends to bridge the gap encountered in the previous works with the modelling of an attention-based DNN model.

3. METHODOLOGY

This section provides an extensive analysis of the proposed $a - DNN$ model, which helps predict cardiac arrest in the earlier stage based on the earlier information of an individual. The learning process helps examine the feature representation, which intends to enhance the quality of prediction accuracy. The simulation is done in MATLAB 2020a environment where various prediction methods like PPV, NPV, specificity, sensitivity and

F1-score. Fig 1 depicts the generic view of the proposed research methodology.

a. Dataset Acquisition

Here, the ECG is recorded from 260 patients during treatment by the cardiologist is anonymized. The data contains 1 min post-shock signal and 9s pre-shock waveform [31]. From all these 260 ECGs, 56 is categorized by the cardiologist, 195 is unsuccessful, and 9 is interderminable. The ECG is provided in digitized forms of ECG amplitude-based time courses noted in text files.

b. Min-Max normalization

It helps normalize the input data where the scale ranges from 0 to 1. It helps to understand the data easily. It is expressed as in Eq. (I):

$$x^1 = \frac{x - \min(x)}{\max(x) - \min(x)} \tag{1}$$

Here, x^1 specifies normalized value, x specifies input value, $\max(x)$ specifies maximal data range, and $\min(x)$ specifies the minimal data range [32].

c. Bounding Box Weight Normalization

To normalize the coordinates, this work considers the pixel values of x and y which marks the boundingbox centre. Then, the value is divided based on the height and weight of the image [33]. It is an easier way to transform data into normalized coordinates. It transforms a quantity in an arbitrary range down to the narrow range, typically from 0 to 1.

d. Ground Truth Definition

Assume that $D = \{z_n\}$ represents the training set to consider a sequence of N cardiac echo groups. Here, every cine series has the recorded heart motion represented by $z_n = \{x_t\}^{|T_n|}$ in the complete cardiac cycles. Every 2D echo frame image is set from the discrete set $L \rightarrow \{-1, 0, 1\}$ with labelled pair l_t . The systolic frame is represented as x_t that is indicated by -1 . The diastolic frame is indicated by 1 . The rest of the "non-critical" frames are represented by 0 in z_n . The synthesized left ventricle volume labels the evert cardiac frames as the ground truth. The function is used to estimate the LV volume, which imitates the decreased volume of monotonic while the systole phase and the when the diastole phase, the monotonic is increased. The training ground truth label is calculated for every cine series z_n .

$$y_{t=} = \begin{cases} \left(\frac{|t - \sigma_{dia}(T)|}{|\sigma_{sys}(T) - \sigma_{Dia}(T)|} \right)^\tau & \text{if } \sigma_{dia}(T) \leq t < \sigma_{sys}(T) \\ n \left(\frac{|t - \sigma_{sys}(T)|}{|\sigma_{sys}(T) - \sigma_{Dia}(T) + 1|} \right)^{\frac{1}{\tau}} & \text{if } \sigma_{dia}(T) \leq t < \sigma_{sys}(T) + 1 \end{cases} \tag{2}$$

Here, the constants are $\eta = 0.8$ and $r = 3$, the selection functions are (T) and (T) to represent the diastolic frame, and systolic frame sequence index represents $l_t = \pm 1$ accordingly. The group of sequence indices represents $T = \{1, \dots, |T_n|\}$. It is important to consider that η should be set as 1 [27]. Here, the η is reduced to project the systolic and diastolic frames. The learning issue comprises the regression problem using the ground truth definition. e. Loss function

The deep learning technique f_{dnn} is used for resolving the mentioned regression issue that is $f_{dnn}(n,)$ during the training stage. The maximum and minimum prediction values frames are selected during the test stage to calculate the diastolic and systolic frames' inference in the cine series [34]. It is expressed in Eq. (III) and Eq. (IV):

$$q_{\tilde{dia}} = \arg \max_t \{y_{(n,t)}\}_1^{|T_n|} \tag{3}$$

$$q_{\tilde{sys}} = \arg \min_t \{y_{(n,t)}\}_1^{|T_n|} \tag{4}$$

There are two components in the training loss function. Mean Squared Error (MSE) is the first component. It is shown in Eq. (V):

$$L_{mse} = \sum_{n=1}^n \sum_{t=1}^{|T_n|} \left| |y_{(n,t)} - y_{\tilde{(n,t)}}|^2 \right| \tag{5}$$

LMSE focuses on lowering the mean of label-prediction difference when Eq. (II) defined the ground truth to encode the mentioned monotonic ventricular volume change. Henceforth, while training, there is no construction for sustaining the monotonic features among the subsequent frames prediction in every cardiac stage [35]. Frames over systolic and diastolic frames are obtained. Predictions that surpass the actual systolic and diastolic frames prediction during the testing stage generate inaccuracy in systolic and diastolic frames localization. While training, the structured loss reinforces the monotonic features to alleviate the problem. It is expressed as in Eq. (VI):

$$L_{MONO} = \frac{1}{N} \frac{1}{|T_n|} \sum_{n=1}^N \sum_{t=2}^{|T_n|} [(1(y_{(n,t)} > y_{(n,t-1)}) \max(0, y_{(n,t-1)} - y_{(n,t)}) + 1(y_{(n,t)} < y_{(n,t-1)} < y_{(n,t-1)}) \max(0, y_{(n,t)} - y_{(n,t-1)})]$$

Here the indicator function represents as 1(.) Eq. (VI) represents the monotonicity during the development of the proposed system, and this equation does not enforce the diastolic and systolic frames' significance concerning the surrounding frames. It is possible to misidentify the surrounding frame like frames are considered for small margins in the series of test cine. Eq. (VI) represents the indirect surrogate in this case, and Eq. (IV) has the inference objective is argued. The global extrema are looked at in the frame predictions of the cine series. The margin among prediction of the diastolic and systolic frame and the largest or smallest predictions of the non-critical frame is imposed to achieve the global extrema. Henceforth, the global extrema (GE) loss function is proposed for L_{mono} substitution that concentrates on promoting the diastolic and systolic frames during the training stage to be the global extrema.

$$L_{ge} = \frac{1}{N} \sum_{n=1}^N [\max((\max(k_n) + \gamma - \gamma_{n, \sigma_{dia}}(T)), 0) + \max(\gamma_{(n, \sigma_{sys})}(T) - \min(k_n) - \gamma), 0)] \quad (7)$$

Here, true index predictions of diastolic and systolic frames are $\tilde{y}_n(T)$ and $\tilde{y}_{n,s}(T)$ accordingly. The non-critical frames (NC) prediction subset is represented by $kn = \{\tilde{y}(n, \sigma_{NC}(T))\}$, the user-defined margin parameter is $\gamma = 0.025$. The L_{mono} dismissed the monotonicity violation on the 15 predictions, and 11 loss components were created and took the 32 as the average that is the frames' number in the cardiac cycle. $|T_n| = 32$ presents the normalization factor in this case in L_{mono} to create the small step size gradient as the signs of training progress. The number of components lost is the reason to reduce the violations. $|T_n|$ is 32. Due to some reasons, this is not optimum. They are (i) the capability of training is degraded by a small gradient to get away the shallow local minima in the landscape loss, (ii) The longer time is needed for training for converging like to resolve more counts that are needed for monotonicity violations indirectly. Here, L_{ge} that needed for optimizing the four most suitable predictions using the large size gradient, and the two-loss components are used to sum. Henceforth, there is no need for normalization

for L_{ge} . With systolic and diastolic frames that are predicted correctly. The L_{mono} have reinforced the violations of monotonicity. Moreover, the objective of the phase-detection issue is not helped directly with the extra information, and then it behaves like a regularizer. Then, the gradient is produced to drive the training is farther from the optimum result. At the same time, the ground truth of systolic and diastolic frames are promoted by L_{ge} . Here, during the training to bear some degree of erratic volumetric evaluation of surrounding frames, these margins are implemented with the model's generalization capability. Lastly, the representation of the training objective is given below in Eq. (8):

$$L_{total} = (1 - \alpha)L_{mse} + \alpha L_{struct} \quad (8)$$

Here, the importance of loss terms is weighted as α , and the proposed model has L_{struct} , either or L_{mono} .

f. Deep Neural Network model (DNN)

The $fdnn$ framework is the proposed system the same as the RNN-related sequential prediction model. The composition of three sub-modules is present in the framework (see Fig 2). They are (i) CNN technique is used for feature extraction of an image, (ii) RNN technique is used to learn the temporal dependencies among the frames of cine series, and (iii) The final prediction is generated by the regression module.

1) Image Feature Extraction by CNN module:

The primary one of $fdnn$, a feature extraction model related to CNN image to create per-frame features $\tilde{x}t = f_{feature}(x_t)$.

2) ResNet Module:

The extraction of images' features $\tilde{x}t$ is explored using using deep residual NN (ResNet) architecture. The stack of residual layers is constituted by ResNet, whether every layer joins the computation block's input with its outputs. The expression of an individual residual layer is presented below in Eq. (IX) and Eq. (X):

$$x_{(t,l)} = x_{(t,l)} + f_{res}(x_{(t,l-1)}; \phi_{feature}^1) \quad (9)$$

and $x_{(t,l)}$ specifies the image feature output of a ResNet and expressed as $x_{(t,l)}$

$$x_{(t,L)} = x_{(t,0)} + \sum_{i=1}^L f_{res}(x_{(t,i-1)}; \phi_{feature}^1) \quad (10)$$

Here, the input features are $x_{(t,l)}$ for the $l \in \{1, \dots, L-1\}$ times residual layer that is with the convolution layer order. Batch Normalization (BN) follows this and the rectified linear activation unit (ReLU). The group of trainable model parameters are represented

as in $\Phi_{feature}^1$ the l^{th} computational block.

a) **DenseNet module:**

DenseNet-based deep learning architecture is another convolutional neural network to be explored in the proposed system. DenseNet layer has the outputs from all the preceding layers compared with ResNet to concatenate for the successive layer (input). \tilde{x}_t of a DenseNet denotes the image features (output) that are given below.

$$x_{(t,L)} = [x_{(t,0)}, x_{(t,1)}, \dots \dots x_{(t,L-1)}] \quad (11)$$

The calculated intermediate layered output is presented below.

$$x_{(t,L)} = f_{dense} ([x_{(t,0)}, x_{(t,1)}, \dots \dots x_{(t,L-1)}]; \Phi_{feature}^1) \quad (12)$$

Convolution layer, ReLU units, and BU units have only one stack. Here, the concatenation operation denotes $[\cdot]$, a customizable computational block representing f_{dense} in the original design. The temporal feature model is the second module to process the complete-featured images using a recurrentneuralnetwork (RNN)

$$h_{(t)} = f_{rnn} (\{x_{(t)}^{\sim}\}_{t=1}^{|T|}; \Phi_{feature}^1) \quad (13)$$

The two general RNN units are tested LSTM and GRU units. A memory cell and three gates are presented in the LSTM, such as forget, input, and output gate. The LSTM unit has the hidden state of computing through controlling information flows using the gates.

$$\begin{aligned} i_t &= s(W_{x\sim t} x_{\sim t} + W_{hi} h_{t-1}) \\ f_t &= s(W_{x\sim f} x_{\sim t} + W_{hf} h_{t-1}) \\ O_t &= s(W_{x\sim o} x_{\sim t} + W_{ho} h_{t-1}) \\ c_{\sim t} &= \tanh(W_{x\sim g} x_{\sim t} + W_{hg} h_{t-1}) \\ c_t &= f_t \odot c_{(t-1)} + i_t \odot c_{\sim t} \\ h_t &= O_t \odot \tanh_{(ct)} \end{aligned} \quad (14)$$

Here, the Sigmoid activation function denotes $s(\cdot)$, $\{W_{\tilde{x}g, hg}\}$ are the variables to denote the weighted parameters for calculating the $c_{\sim t}$, which refers to hidden state candidates. $\{W_{\tilde{x}i, hi}\}$ are the variables to denote the weighted parameters for calculating the input gate that manages the $c_{\sim t}$ influence to the ct , which represents the internal memory state. $\{W_{\tilde{x}f, hf}\}$ are the variables to denote the weighted parameters for calculating the f_t , which represents the forget gate that manages the combination of current memory state c_t and the previous memory state $c_{(t-1)}$. The weighted parameters are $\{W_{\tilde{x}o, ho}\}$ for calculating O_t that represents the output gate that manages the current state c_t exposure to the outside networks. Eq. (13) to Eq. (18) represents the biased terms to avoid further clarity.

b) **GRU module:** The distinction between the LSTM unit and the GRU unit is the major feature considered the simplified gating technique. The computation of GRU units' hidden state is presented below.

$$\begin{aligned} z_t &= s(W_{x\sim z} x_{\sim t} + W_{hz} h_{t-1}) \\ r_t &= s(W_{x\sim r} x_{\sim t} + W_{hr} h_{t-1}) \\ h_{\sim t} &= \tanh(W_{x\sim g} x_{\sim t} + W_{hg}(r_t \odot h_{t-1})) \\ h_t &= (1 - z_t) \odot h_{(t-1)} + z_t \odot h_{\sim t} \end{aligned} \quad (15)$$

The update gate denotes as z_t to decide the candidate state \tilde{h}_t and the previous state $h_{(t-1)}$ composition for representing the unit h_t which is hidden state unit. This state presents the input gate simplification, and the LSTM has the forget gate. The weighted parameters $\{W_{\tilde{x}z, hz}\}$ are assigned to z_t , the update state. The weighted parameters are $\{W_{\tilde{x}g}, W_{hg}\}$ for computing \tilde{h}_t . The weighted parameters $\{W_{r\tilde{x}}, W_{hr}\}$ for computing the r_t , a reset gate that permits the computation of candidate state to drop the unwanted old information eventually.

It allows for a more compressed presentation. Eq. (19) to Eq. (22) represents the biased terms for avoiding clarity. There are two gates in the GRU unit that are contrasted to the design of three gates in the unit of LSTM that represents the low amount of model parameters needed by GRU. It is calculated quickly provided a similar amount of units that are required.

c) **Bidirectional GRU/LSTM modules:**

A traditional recurrent neural network unit has the information of the prior state that is the segment of calculating the present state in every step. The separate "backwards" state is maintained in the bidirectional recurrent neural network variants on the secondary controller that are added on the first controller to the "forward state". The second controller reads the sequence of input in reverse order from the implementation viewpoint that is the calculated image features of the convolutional neural network for calculating the backward state. The element-wise sum operation combines the outputs of two controllers for presenting the bidirectional recurrent neural network outputs in every step. In the investigation, the bidirectional variation is tested on both GRU and LSTM units to compare comprehensively.

d) **Regression Module:** The final prediction of every frame produced by the regression model is represented as $y_{\sim t} =$

$f_{regression}(\{h_t\}_{t=1}^{|T_n|}; \Phi_{regression})$. Backpropagation Through Time (BPTT) is adopted to update the

parameters during the framework training.

g) Bellman Equation:

Here, Bellman Equation (BE) is considered for measuring the individual state during cardiac arrest. It is essential to determine the state value s , $V\pi(s)$ with s' state value (s') in an iterative manner. Here, the state values are evaluated based on the action-value function and it is expressed in Eq. (23):

$$Q_{\pi}(s, a) = \sum_{s^1} p_{ss^1}^a (r, (s, a) + \gamma \cdot \sum_{a^1} \pi(a^1 | s^1) \cdot Q_{\pi}(s^1, a^1)) \tag{16}$$

Based on Eq. (23), the state-action pair is predicted recursively following the policy π . The state-value function (s') is equal to the action-value function (s', a') of successive actions a' which is multiplied with the policy probability of choosing an action $\pi(a'|s')$ as expressed in Eq. (24):

$$Q_{\pi}(s, a) = \sum_{s^1} p_{ss^1}^a (r, (s, a) + \gamma \cdot V_{\pi}(s^1)) \tag{17}$$

The objective is to exploit the total cumulative reward during the successive runs. This policy enhances the total cumulative reward is termed as optimal policy. The optimality π' is determined to be superior to or equal to policy π iff $V\pi'(s) \geq V\pi(s)$ for successive states s . The optimal policy π^* fulfills $\pi^* \geq \pi$ for all optimal policies. It is guaranteed to exist; however, it is not unique. There are various optimal policies; however, it shares all the value functions, i.e. optimal value functions. It provides maximal value compared to other value functions as shown in Eq. (25):

$$V_x(s) = \max_{\pi} V_{\pi}(s) \tag{18}$$

Here, $v^*(s)$ specifies the maximal reward for s state. The optimal value function specifies the maximal reward with action a , and it is expressed as in Eq. (26):

$$Q_*(s, a) = \max_{\pi} Q_{\pi}(s, a) \tag{19}$$

The attained state value (individual) is equal to the maximal action value and it is expressed in Eq. (27) and Eq. (28):

$$V_x(s) = \max_{\pi} V_{\pi}(s) \tag{20}$$

$$Q_*(s, a) = \max_{\pi} Q_{\pi}(s, a) \tag{21}$$

h) Optimality measure based on Bellman Equation

The optimality measure is provided based on the state value function in s which is equal to the action. It provides the maximal probable immediate reward along with the long-term reward of successive state s' . It is expressed in Eq. (29):

$$V_*(s) = \max_{a \in \sum p_{ss^1}^a} (r, (s, a) + \gamma V_*(s')) \tag{22}$$

The optimality is proven based on the Eq. (30):

$$Q_*(s, a) = \sum_{s^1} p_{ss^1}^a (r, (s, a) + \gamma \cdot \max_{\pi} Q_{\pi}(s^1, a^1)) \tag{23}$$

The Bellman equation acts as a keystone to predict the optimal values and attain every layer's optimal policy. The state action of an individual is measured using the proposed GEO discussed in section given below.

Golden Eagle Optimizer (GEO)

The proposed Golden Eagle Optimizer (GEO) is based on the existing Eagle Search Optimization (ESO) designed based on the searching behaviour of the eagle during the hunting process, as in Fig 3. It is divided into three diverse phases: space selection, space searching, and prey swooping.

i) Space selection

The golden eagle selects the space randomly based on the previous search information (previous cardiac information of an individual). It is expressed in Eq. (31):

$$p_{new,i} = p_{best} + \alpha * \gamma (p_{mean} - p_i) \tag{24}$$

The α parameter for managing the position change is formulated using the above equation indeed of a fixed value. It is shown in Eq. (32):

$$\alpha = \frac{\alpha * (max_{iteration} - t + 1)}{max_{iteration}} \tag{25}$$

This parameter influences the eagle position and improves the exploitation and exploration of the proposed technique. Here, r specifies random values among 0 and 1, p_{best} and p_{new} are the current and new search spaces. p_{mean} specifies that the eagles have consumed the essential information from the previous points.

ii) Search stage

After the search space selection from the previous step, the eagle initiates the search for prey over the space by moving the spiral shape to fasten the search. In the searching stage, the eagle position is updated expressed in Eq. (33):

$$p_{i,new} = p_i + y(i) * (p_i - p_{i+1}) p_{best} + x(i) * r(p_i - mean) \tag{26}$$

$$x_i = \frac{xr(i)}{\max(|xr|)}, y(i) = \frac{yr(i)}{\max(|yr|)} \tag{27}$$

$$xr(i) = r(i) * \sin(\phi(i)), yr(i) = r(i) * \cos(\phi(i)) \tag{28}$$

$$\phi(i) = \alpha * \pi * rand \tag{29}$$

$$r(i) = \phi(i) * R * rand \tag{30}$$

Where α specifies the parameters that consider value

from 5 to 10, and R specifies the parameter that targets the value from 0.5 to 2.

iii) Swooping stage

In the swooping stage, the eagle initiates the move from the best search position towards the prey in the swing movement as depicted in Eq. (34):

$$p_{i,new} = rand + x_1(i) * (p_i - c_1 * p_{mean} + y_1(i) * (p_i - c_2 * p_{best})) \quad (31)$$

$$x1(i) = \frac{xr(i)}{\max(|xr|)^r} \quad y1(i) = \frac{yr(i)}{\max(|yr|)^r} \quad (32)$$

$$X(i) = r(i) * \sinh[(\theta(i))], \quad yr(i) = r(i) * \cosh[(\theta(i))] \quad (33)$$

$$\theta(i) = \alpha * \pi * rand(i) \quad (i) \text{ Where } c1, 2 \in [1, 2]. \quad (34)$$

4. RESULTS

This section extensively analyses the numerical outcomes attained using the proposed prediction model. Here, metrics like specificity, sensitivity, F1-score, NPV and PPV are the factors for evaluating performance. The sensitivity and PPV are used to evaluate the performance using various statistical measures. The outcomes of data prediction have four types. They are (i) false positive (FP): in the cases of non-cardiac arrest, the cardiac arrest needs to be predicted, (ii) true positive (TP): in the cases of cardiac arrest, the cardiac arrest needs to be predicted, (iii) true negative (TN): in the cases of non-cardiac arrest, the cardiac arrest cannot be predicted, and (iv) false negative (FN): in the cases of cardiac arrest, the cardiac arrest cannot be predicted that has the false-negative value is high, and the sensitivity is low. Eq. (35) represents the calculation of Positive Predictive Value (PPV) is represented below.

$$PPV = \frac{TP}{TP+FP} \quad (35)$$

Here, Eq. (35) represents the calculation of Negative predictive value (NPV) below.

$$NPV = \frac{TN}{TN+FN} \quad (36)$$

Eq. (36) is used to calculate sensitivity which is given below.

$$sensitivity = \frac{Tp}{Tp+FN} \quad (37)$$

Eq. (37) is used to calculate specificity, given below.

$$specificity = \frac{TN}{TN+FP} \quad (38)$$

Sensitivity and the PPV have weights in the classification case, and Eq. (39) is used to calculate the F1 score. The sensitivity and PPV are weighted in the ratio of 1:1.

$$F1 - score = 2 * \frac{PPV * sensitivity}{PPV + sensitivity} \quad (39)$$

5 CONCLUSION

The prediction of cardiac arrest at the earlier stage helps prevent earlier death. The proposed DL-based classification model assists in predicting the factors of cardiac arrest. The proposed $a - DNN$ model works well in providing better prediction accuracy than various existing approaches. The finest classifier model helps the cardiologist predict the factors that trigger cardiac arrest at the earlier stage. Here, an available online dataset is considered composed of ECG signals with systolic and diastolic frames. The pre-processing helps normalize the data within a range of [0, 1] and fed as an input to the classifier model. The proposed deep classifier model performs feature representation, and the weighted analysis is done with the Bellman Equation. The attained weighted value is optimized using the proposed GEO model, which fulfils both exploitation and exploration. The optimal outcomes are acquired with better convergence and fitness function. The performance of the anticipated model is compared with various approaches like RF, DT, LR, LSTM, GRU and hybrid approaches. The model attains 95% PPV, 99.5% NPV, 99% sensitivity, 99.8% specificity and 98% F1-score. The major limitation relies on the lack of analysis with the error rate and execution time. However, these two metrics will be more important in future research to help the upcoming researchers.

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